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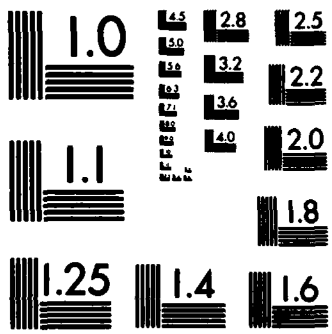

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THE USE OF TIME SERIES ANALYSIS TO DEVELOP SPARES REQUIREMENTS FORECASTS

Larry D. Taylor, GS-11

LSSR 94-83

DEPARTMENT OF THE AIR FORCE
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SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER LSSR 94-83	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) THE USE OF TIME SERIES ANALYSIS TO DEVELOP SPARES REQUIREMENTS FORECASTS		5. TYPE OF REPORT & PERIOD COVERED Masters Thesis
		6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s) Larry D. Taylor, GS-11		8. CONTRACT OR GRANT NUMBER(s)
9. PERFORMING ORGANIZATION NAME AND ADDRESS School of Systems and Logistics Air Force Institute of Technology, WPAFB OH		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS
11. CONTROLLING OFFICE NAME AND ADDRESS Department of Communication AFIT/LSH, WPAFB OH 45433		12. REPORT DATE September 1983
		13. NUMBER OF PAGES 120
14. MONITORING AGENCY NAME & ADDRESS(if different from Controlling Office)		15. SECURITY CLASS. (of this report) UNCLASSIFIED
		15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

Approved for public release: IAW AFR 190-17.

LYNN E. WOLAVER
Dean for Research and Professional Development
Air Force Institute of Technology (ATC)
Wright-Patterson AFB OH 45433

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

Demand
Demand Rates
Forecasting
Requirements Forecasting
Time Series Analysis

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

Thesis Chairman: Herbert A. Stewart, Major, USAF

DD FORM 1473, 1 JAN 73 EDITION OF 1 NOV 65 IS OBSOLETE

UNCLASSIFIED

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

There is a growing suspicion that a linear relationship for demands per flying hour, as currently used, is not an accurate assumption. The spare parts data used for stock level maintenance may not, necessarily, conform to the general assumption of a linear relationship for demands on those parts per flying hour. There is a concern that support based on this peacetime assumption may fall short in a wartime situation. Demands per flying hours are inherently a factor of time, but this factor is not presently considered in computing forecasts. Time series methods are compared to a model of the same data, produced without the benefit of time series methods, to demonstrate that using the "linearity assumption" in forecasting can lead to errors.

LSSR 94-83

THE USE OF TIME SERIES ANALYSIS TO DEVELOP SPARES REQUIREMENTS FORECASTS

A Thesis

Presented to the Faculty of the School of Systems and Logistics

of the Air Force Institute of Technology

Air University

In Partial Fulfillment of the Requirement for the

Degree of Master of Science in Logistics Management

By

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September 1983

This thesis, written by

Mr. Larry D. Taylor

has been accepted by the undersigned on behalf of the faculty of the School of Systems and Logistics in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE IN LOGISTICS MANAGEMENT

Date: 28 September 1983

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CHAPTER 1

INTRODUCTION

Background

An ever growing concern of the U.S. Air Force is the question of whether our forces are well enough equipped and trained to maintain the deterrent stature that the United States has enjoyed for so long. If the United States should have to go to war, then how well will the peacetime planning support and sustain our forces? Peacetime planning and training is based on a "best estimate" of what we might expect to face in the "next war." The increasingly complex weapon systems, designed to counter the threat of potential enemies, make the problem of supporting and sustaining forces more acute than ever before in our history. Faced with the additional constraint of limited funds to support a weapon system, the Air Force must be able to procure the materials necessary to support the forces in the most effective manner possible.

The cost of a weapon system is so high that it is virtually impossible, as well as impractical, to have a "one of everything" type of supply system to support it. The limited funds available to the Department of Defense (DoD) for support and maintenance of its weapon systems, requires that

prudent judgement be exercised when considering what and how much to buy. A large percentage of the dollars spent during the life of a weapon system are for its maintenance and replacement or repair of parts.

The nature and purpose of a weapon system demand a design such that individual components can be quickly removed and replaced to minimize its down time. These components are often expensive, and constitute a large portion of the cost of the system. The complexity of the components also means that maintenance or repair is costly. The Air Force has categorized components into two kinds of items, namely, consumables and recoverables.

Consumable items are either consumed in use or otherwise lose their identity by incorporation into another assembly. They are generally low cost and most often supplied in economic order quantities (EOQ). Recoverable items are generally high cost, retain their individual identity (usually via serial numbers), and are repairable or reuseable. This group of items is further broken down into Line-Replaceable-Units (LRU'S), which can be removed and replaced, as a unit, to correct a deficiency or malfunction of a weapon system (or other major items such as equipment). These are broken down into Shop-Replaceable-Units (SRU's), or sub-components making up LRU's. The terms LRU and component will be used synonymously in this thesis.

The LRU's and SRU's are repairable at various levels of maintenance, i.e., operational (base), intermediate and de-

pot. Base level maintenance is that level of maintenance determined to be within the capabilities of an operating base or wing with its assigned skills and equipments. Intermediate level maintenance is normally accomplished at the major command level. It may be performed at a fixed or mobile location, within the geographic area of the command and may be collocated with an operating base. Depot level maintenance is a more specialized maintenance which consolidates highly technical skills and specialized equipments for major repair and modification of systems and recoverable items. After the initial procurement of a weapon system, the depots are responsible for maintaining the overall supply and distribution of spare parts and materials for logistic support of assigned weapon systems, or equipments, for their useable life. This includes the additional procurement of LRU's and other parts to maintain a determined level of usage.

Resource Determination

Demands per flying hour data is currently being used by the Air Force to forecast spares requirements. The development of complex, dynamic, computer models to assist in the management of resources has given rise to the question of how accurate forecasts based on this data really are. Demand per flying hour (D/FH) is a statistic based on the requirement to replace some part on an aircraft after a specified period of operation. This period, measured in flying hours,

and the demand ratio are projected according to the historical number of replacements for each individual component. Most computations of stock levels assume a steady state with constant demand and service rates exists. The assumption has proven both reasonable and convenient during peacetime (11:8).

When calculating the level of stockage for an item, the general assumption has been a 1:1 linear relationship between its demand and flying hours. That is, as the historical records of components are compiled, and the data is averaged over the cumulative flying hours for a fleet of aircraft using that component, the resultant computation shows that "X" number of components have been requisitioned for every "X" number of flying hours. The relationship of demands on an LRU as a function of flying hours has important bearing on the stock level of that LRU.

The forecasts use mathematical models calibrated with data collected in a peacetime operational environment. For the most part, this D/FH ratio has been adequate. This ratio could, conceivably, be less linear than the relationship generally assumed for the peacetime weapon system. Some preliminary investigations argue that breaks per flying hour will be sublinear ("aircraft get better the more they are flown") for some components and superlinear (parts fail more the more they are flown) for others (8:6). These investigations have examined 'war games' or surge exercises (intended to be as realistic as possible), for their overall affect on sup-

ply and found that, "Overall, total demands per sortie were comparable to (lower than, etc.) normal peacetime flying (8:6)." A surge exercise is designed to demonstrate a unit's ability to sustain the high level of flying activity that may be expected in war. It seems intuitive that a wartime environment should place different levels of demands on the inventory system than peacetime.

Problem Statement

Many maintenance personnel who have worked with specific systems for some time believe that as their aircraft get more and steady usage that the rate of failure for components is less, or sometimes more, frequent than the supply system provisions for (8:6). If in fact the D/FH ratio is other than 1:1, a more accurate forecasting method should provide dollar savings, as well as enhance the availability and readiness of aircraft.

The spare parts data used for stock level maintenance is based on a steady state, constant demand, peacetime environment, which lends itself to the present usage of a 1:1 linear ratio for the D/FH for stock levels. The data is made linear by using the equation $Y_t = a_0 + a_1 X_t + e_t$ which is essentially the same as that for a straight line. Here Y_t is the demand at period t, the a_i's are the values of the observations at X_t, which is the value of the flying hours at period t, e_t is the error factor (17). (This type of notation is used throughout the thesis). The demand data is accumulated

and is then divided into the cumulative flying hours which gives a linear, 1:1 ratio. With the emphasis on the more realistic, dynamic world, this "linearity" may not hold true. The data is time related, and the calculations used in the stock leveling do not take this into consideration.

There are many computerized models and forecasting methods available now that theoretically should provide a more accurate forecast for spares. This thesis proposes to show that time series analysis is a more accurate method than using the linear assumption. Time series analysis is a powerful forecasting method that takes into consideration, besides the time factor, such things as seasonal fluctuation in demands. It is able to analyze data in the manner that it actually occurs so the forecast figure will account for the fluctuations, seasonality and other time related facts that influence a forecast of future requirements.

Research Objectives

This study will use time series analysis with selected F-16 LRU data and demonstrate a method of forecasting future requirements for those parts. The method is applicable to any similar time related data. An additional outcome of the study is the intent to demonstrate that the number of demands per flying hour is not a linear ratio. Therefore, the present methods of forecasting requirements may not provide the most cost effective forecast, nor provide the Air Force with an optimal spares stockage.

Justification

"The objectives and assumptions employed in every stage of the resource allocation process ought to be consistently derived from system-level, output-oriented goals (9:7)."

This study supports the effort to better manage spares and repair parts; and therefore, better support the using activities. The premise of this thesis is that spare parts required to maintain an aircraft may not, necessarily, conform to the general assumption of a linear relationship for demands on those parts per flying hour. Spare parts, or the lack thereof, has always been an issue of concern, causing the problem of allocating shortages, rather than resources, because requirements inevitably exceed funds availability.

An improved forecast might alleviate shortages, improve availability of ready aircraft, and allow funds to be spent in a more efficient manner. The demands for parts and the flying hours are inherently a factor of time, but this factor is not presently considered in computing forecasts. Requirements inevitably grow over time, while at the same time funds availability tends to decline, which puts pressure on the managers to delete unjustified requirements (9:9). All of this lends itself to the need for more accurate forecasting, so that the required parts are available while funds are judiciously spent.

Research Question

There is a small amount of literature and a growing suspicion that a linear relationship (demands per flying hour), as currently used, is not an accurate assumption. Some current research of the Rand Corporation has clearly demonstrated that, at least for some LRU's, the demands per flying hour is not a linear ratio. Time series analysis, on the other hand, does not rely on cumulative averages, but uses the actual data as it occurred through time for making forecasts. This thesis responds to the question of whether a better method to forecast spares exists, and if so, how much improvement can be achieved in forecasting? In attempting to answer this question, the method to arrive at a correct ratio for the demands per flying hour to use in forecasting future requirements will be demonstrated. The method can be applied to any aircraft or system that has accumulated data over time.

Scope and Limitations

To accomplish the study, five LRU's, which were among the "top ten" items impairing the F-16 mission capability (MICAP) for the week of 12 June 1983, will be used as the data base. The fact that these LRU's are MICAP items implies that, for what ever reason, the original spares forecast proved inaccurate. These five LRU's provide ample data to demonstrate the method of time series forecasting spares re-

quirements. Appendix A contains a listing of the LRU's by work unit code (WUC), actual flying hours (by month, 06/79 to 04/83 inclusive), and the removals or demands for the LRU's each month. This is the same type of data that would be accumulated and averaged to get the linear ratio for the current forecasting method.

Methodology

The Box-Jenkins method of time series analysis will be used for this thesis. Time series analysis of data which include an independent variable (flying hours) and a dependent variable (demand) is accomplished using a transfer function. Each variable is first prewhitened by fitting an appropriate model to the data. Prewhitening is done to clarify the relationship between flying hours and demand.

> For a given pair of series, there are interrelationships between the series and intrarelationships within the individual series. The intrarelationships are summarized in the autocorrelation structure of the individual series [15:378]

The prewhitened model, then, has all the autocorrelation within the series removed and only "white noise" remains. White noise is analogous to a series that is completely random, i.e., there is no pattern whatsoever contained in the series. This is necessary before the interrelationship, or cross correlation, between the variables can be found. After a prewhitened model is accomplished for both the variables they are combined into a single transfer function model to

find the best fit. In general, the models are developed in three stages, i.e.; model identification, parameter estimation, and then a forecasting model. These stages will be described in more detail in chapter three.

Preview

The remainder of this thesis will include a review of the literature (chapter 2) pertaining to the "linearity" issue. The methodology (chapter 3) of obtaining the time series models follows and contains a comparison of the time series models with a model (called the 'old method') of the type which is presently used. Conclusions, findings, and recommendations will conclude the thesis effort.

CHAPTER 2

LITERATURE REVIEW

This review starts with a look at how spare parts are determined for the support of a weapon system, and will be followed by a review of the current literature documenting research on some of the problems encountered providing this support. Finally a section on time series analysis and why it should be considered as part of the solution to the support problems will be presented.

THE SPARES DETERMINATION PROCESS

Interim Contractor Support

During the development phase of a weapon system, design modifications and changes can occur frequently until the updated requirements for the system are met. As a part of the contract, the contractor is usually assigned Interim Contractor Support (ICS) during the demonstration and validation (D&V) phase and until the Air Force is able to organically support the weapon system (2:1). The Air Force Program Manager (PM) and the Deputy Program Manager for Logistics (DPML) analyze the risk of the components (i.e., to defer total investment until after the D&V phase or until

the design is stabilized), to determine which components should be assigned ICS. This list of ICS components is further refined during the full-scale engineering development and contracted for during the production and development phase (2:9).

Initial Provisioning

The initial provisioning of parts for a new weapon system is developed after the contract to build the system has been awarded. Initial provisioning is defined in AFLCR 65-5 as a "management process for determining and acquiring the range and quantity of support items necessary to operate and maintain and end item of material for an initial period of service (1:1-1)." The initial period is defined "to begin with the preliminary operational capability of the weapon system through the lead time required for the component, plus three months, or a 12 month minimum (1:1-1)." This initial provisioning is designed to give adequate parts support until normal resupply is established. During this time the contractor and the Air Force jointly determine the items that have to be provisioned.

All parts of the weapon system are reviewed for current availability in the Air Force inventory. If items are available, the Item Manager (IM) is informed so that stock levels can be adjusted upward for the additional requirements. Items not currently in Air Force inventory are assigned National Stock Numbers (NSN) and assigned to an IM for pro-

curement and subsequent management. Where an item is already in the inventory, the present demand data is already established and only needs adjustment based on initial forecasts.

The items that are new to the Air Force do not have an established demand and must be initially provisioned so they are available for use when the weapon system becomes operational. Consumable (EOQ) items are provisioned based on estimates using demand information from similar items currently in the inventory. The recoverable items not currently in the inventory are provisioned based on a combination of factors gained from the contractor and factors developed by an Air Force equipment specialist. The contractor furnishes such data as the items mean time between failures (MTBF), the mean time to repair (MTTR), the replenishment cycle time (RCT) and, the lead time for procurement (3). The equipment specialist uses this information to develop the initial maintenance requirements. The demand rate for the item is initially established through the compilation of this data.

Initial Spares Support List

The Initial Spares Support List (ISSL) is a listing of recoverable and consumable line items used in the repair of the recoverables. It is intended to include the parts necessary for base level maintenance. The ISSL is developed by the depot, which is an Air Logistics Center (ALC). It is developed during the provisioning phase and is based on inputs from the contractor, the IM, the System Manager (SM)

and, the using command that will "own" the weapon system (14). The quantity of recoverable items on the ISSL is the additive factor of the base order and shipping time and the base repair cycle time quantity (19). Consumable quantities are based only on the base order and shipping time quantities. The ISSL quantities are put into the Standard Base Supply System (SBSS) computer as the initial demand level. This demand level, after two years, is adjusted based on actual demands for the parts.

Demand Levels

The demand levels for recoverable items are determined by the SBSS, by adding the base repair cycle quantity, the order and shipping time quantity, the quantity not repairable this station (NRTS) condemnation rate, plus a safety stock level. To this figure a +0.5 adjustment factor is added for items costing $750.00 or more, and a +0.9 adjustment factor for those costing less (1). The base level demands are forwarded to the ALC responsible for the weapon system. There, each independent asset requirement is consolidated into the Recoverable Consumption Item Requirements System, the D041. Inputs to the D041 include major command (MAJCOM) flying hour projections for five years, and inputs from each base SBSS which gives the recorded failures to date. The failure rates are applied to total flying hours to get a historical failure per flying hour rate. The failures are then applied to the quarterly flying hour projections to

obtain an estimated number of item failures per future quarter. The item's NRTS condemnation rate is subtracted from the projected number of item failures to generate an item-buy recommendation. Any remaining failures are coded as repairs. The provisioning and War Readiness Materials (WRM) requirements are input from other automated systems. WRM is defined as those assets, in addition to normal peacetime operating stocks (POS), needed at the start of a conflict to support active forces until industrial production can sustain combat requirements (4:1). All other sources of requirements are manually input by the IM. These include Foreign Military Sales (FMS), retrofit requirements, non programmed requirements, training and testing requirements and the ISSL.

CURRENT RESEARCH

This issue of "linearity" led to this study to define a better model to use in forecasting future requirements. A correct time series model will eliminate some of the causes of linearity. This thesis is mainly concerned with the methodology of using time series methods as a better tool in forecasting demands, or removals, for spare parts. Although there does not appear to be literature that specifically addresses this issue, there is a limited amount of literature that does address the linearity issue. The linearity

issue and this study are both interrelated in that the assumption of linearity, no matter what the form, is the cause for many of the logistic support problems being encountered today. It is something that has attracted the attention of researchers who are looking both for reasons why material support is not as good as it might be and for better ways to maintain the weapon systems.

The subject of 'linearity' is a complex one. Only relatively recently in the research is it specifically addressed. There are several references that indirectly refer to it and some recent unpublished Rand Corporation studies are more specific about how the linearity of demands per flying hour could play a part in spares computation.

None of the literature reviewed discusses the time factor, which is an integral part of the data collected for Air Force requirements, because it is collected over time. The literature does discuss the interrelationships of how the resource requirements system as a whole is affected by the nebulous assumption of linearity. However, this thesis is more concerned with finding an accurate model to forecast time related data, than with the actual degree of "linearity" as it is discussed in the literature.

The findings of the researchers demonstrate that the ratio of demands per flying hour do change. They also show that the ratio is not a linear one, for the components investigated (7,8,9,10,11,12,16). Embry and Crawford make specific reference to the issue of "linearity" and it's rela-

tion to the overall Air Force requirements. They define the more general type of problems the issue of linearity poses.

> Peacetime experience is commonly used to develop component demand rates (expressed in removals per flying hour) for use in peacetime spares requirements computations. This same rate is used as an input to wartime resource requirements and capability assessment models based on the assumption that removals are proportional to flying activity. Since both requirements and capability estimates are sensitive to the demand rate parameter, they are also sensitive to this "linearity" assumption [10:iii].

Sortie Length and Linearity

Embry and Crawford (10) examined a number of past studies that indicate the "linearity" assumption is tenuous when applied across operations having different sortie lengths. Also, some studies suggested the assumption may not be valid across periods with different sortie rates. Their key point was that if the "linearity" assumption is not valid, capability assessments that rely on it must be inaccurate, and that requirements statements that rely on this assumption may produce the wrong mix of resources to support wartime operations.

> Both requirements computation and capability assessment require assumptions to support extrapolation of peacetime experience to wartime levels and patterns of activity. Most of the logistics models that are currently being used for developing resource requirements and assessing capability assume component demands are a function of flying hours. Since both types of estimates are particularly sensitive to this demand assumption, it is important that demand rate estimates be accurate. The "linearity" assumption, which holds that doubling the level of flying activity will double the demand for components, has significant resource implications and is a potential source of bias in capability projections [5:1].

The requirements computation for spares, as described above, considers the reported removals of an item as part of the calculation. Removals happen for a myriad of reasons, failure being the most important. It is often the case that the failure cannot be duplicated (CND) in the shop environment, but the removal is still recorded. Embry and Crawford point out that, "It is important to note that peacetime demand rate measures removals, not failures (10:3)." However, the removal and demand rate are considered synonymous when calculating spares requirements. The methodology chapter of this thesis will use removal data for selected F-16 LRU's to demonstrate the forecasting technique. This will not provide the total solution to the linearity problem because the assumption that removals are proportional to flying hours is not an accurate one. The time series model will demonstrate this, and demonstrate its utility by showing a way to "get around" this linear assumption.

Embry and Crawford make a point where this assumption has been used that, "If expected wartime removals are not strictly a function of the peacetime demand rate and wartime flying hours, both requirements estimates and capability assessments are affected (10:4)". The best solution then, would appear to be that "...of improving the basis for both types of estimates (10:4)"

Eight different studies that deal with linearity were discussed in the paper by Embry and Crawford. In all of the

studies the changes in sortie length and rate were the most important variable in the observed changes in demand rate. When comparing the demands during the SALTY ROOSTER exercise at Hahn Air Force Base with the rates during the previous year, Crawford found significant changes in a number of components. The removal rates ratio varied from .33 to 2.7, with the higher rates belonging to items that are not exercised extensively in peacetime but stressed more under exercise conditions. Other demand ratios dropped to a third of the peacetime ratios (10:8). In another test of F-16 data, the ratio of surge to control period malfunctions per sortie on the Fire Control and Weapons Delivery System were examined. Once again they found that the ratio varied from -.3 to 1.6 when the sortie rate went from .84 to 3.44 sorties per day. The inertial navigation system (INS) experienced a 1.6 ratio of removals and all other dropped below the control average (10:14). They concluded that their findings reinforced the earlier research, suggesting that changing utilization of the aircraft affects the demand rates (10:20).

All of the research indicates that there are problems with using the assumption of linearity to calculate the demand rates needed for forecasting requirements. Because the demand ratio is found to vary, rather than remain at a fixed ratio, the assumption becomes expensive in terms of cost and parts shortages. It also indicates that the mix of support parts intended to support wartime activities may not include

the parts that will be required, in the quantities required. The spares kits may be over stocked with some items and under stocked with others; and if the research proves correct the more expensive, long lead time items are those that will be short.

Inconsistencies in Readiness Goals

In September 1982, Embry (8) presented a briefing to the DoD Material Readiness and Sustainability Symposium in which he stressed, "... the need for analyses and management actions that recognize the interdependencies of various elements of the aviation logistics support system (9:iii)." He stressed that the outputs of these interdependencies be tied to aircraft oriented wartime performance measures. The management and analyses actions that concern the resource readiness issue involve program adequacy, the effects of alternate funding levels, and feedback and control. The feedback and control phase is where Embry's concern was stressed most. "The problem during this phase is generally more one of allocating shortages, not resources, because requirements inevitably exceed funds availability, particularly when requirements change (9:6)." This problem of requirements change is due, in part, to fluctuations in the demand rates which were discussed earlier. Changes in requirements after the determination of the funding level make attainment of readiness goals nearly impossible.

These goals are used to guide management as well as size

resource requirements. The failure to meet the goals, is where the challenge to logistic managers is the greatest. Embry's comment about some of the reasons for this failure is appropriate here:

> There are no clear links between intermediate performance measures, such as supply fill rates or maintenance manpower utilization, and wartime sortie generation capability. Yet these functional goals are the basis for resource requirements computations. Because they are not linked to output measures, inconsistencies in the assumptions used to size various functional requirements are not only possible, but unfortunately fairly common [9:6-7].

The key point that he makes is that, "...the objectives and assumptions employed in every stage of the resource allocation process ought to be consistently derived from system-level, output-oriented goals (9:7)." He defines the real outputs as those that, "...are reflected in weapon system readiness, not supply demand satisfaction or maintenance production rates (9:9)." The ideal demand forecast would allow supply demands to equal the requirements that are reflected in weapon system readiness. However, because the resource requirements must be identified so far in advance, to meet budgeting requirements it becomes difficult to forecast accurately, the proper mix of items to buy. This is even more apparent when the demand for those items is not the same as was assumed when the forecast was made. When the forecast does not meet the weapon system readiness requirements, readiness suffers.

Demand Rates and the Linearity Assumption

Kamins and Crawford (12) defined the relationship between linearity and demand rates, and how they are used.

> Peacetime experience is commonly used to develop component demand rates (expressed as removals per flying hour) for use in peacetime spares requirements computations. This same demand rate is used as an input to wartime resource requirements and capability assessment models, based on the assumption that removals are proportional to flying activity. Because both requirements and capability estimates are sensitive to the demand rate parameter, they are also sensitive to this "linearity" assumption [12:iii].
>
> If this "linearity" assumption is not valid, capability assessments that rely on it are inaccurate. Perhaps more important, requirements computations that rely on this assumption may produce the wrong mix of resources to support wartime operations [12:iii].

Rand studies done prior to the Kamins and Crawford study have documented decreases in maintenance actions per flying hour (MAPFH) that seem to occur whenever aircraft fly longer sorties. But, they point out, these apparent decreases are ignored when computing war readiness requirements. One of the reasons these decreases are ignored is the assumption that MAPFH will double if flying doubles. They also point out that this generally conservative assumption results in War Reserve Material (WRM) kits that give more capability than would kits based on contrasting studies (12:iv)

Because funding for spares is austere, the component buys often result in less of the more expensive LRU's and more of less expensive repair parts. So it is necessary that the correct requirements are identified initially. This is noted by Kamins and Crawford:

> The argument that the linearity assumption results in a WRM kit with more capability may be fallacious: When maintenance factors require large numbers of expensive LRU's, policy decisions mitigate the dollar requirements so that the kits will be affordable [12:iv].

No matter how expensive a WRM kit is it must have the proper mix of parts or it will not give the desired results in terms of capability . "Arbitrary policy decisions designed to reduce high WRM kit costs are likely to make the mix even worse (12:v)." Because of this fact the issue of linearity becomes a central focus. Whether failures in aircraft systems (particularly those requiring parts replacements) remain constant, when the environment changes from peace to war, is the issue that must be dealt with.

Kamins and Crawford cite a Boeing study which analyzed maintenance data on B-52D operations in Southeast Asia. The findings of that study found that "...the landing gear system sub-linearity was so pronounced as to decrease total failures when sortie rates were increased (12:1)."This supports the findings of studies mentioned earlier that the linearity assumption may lead to incorrect buys and support will become faulty. Another study cited, by the Rome Air Development Center, showed that higher levels of flying activity were associated with measurable increases in the observed MTBF for all types of aircraft studied, including tactical (12:2).

At the Third Logistics Capability Assessment Symposium, in March 1983, Crawford (7) reviewed the excessive variation

in empirical demand rates for some important aircraft components. This is a "...poorly understood phenomenon that is potentially very important to logistics capability assessment and requirements determination (7:iii)." He first described the Poisson arrival process, and then related that to the way requirements and capability assessment models use them. These models make the assumption that the time between failures is an exponential random variable and within this binomial approximation the sorties are independent.

Crawford pointed out that the observed variations in the LRU's he checked are not consistent with a Simple Poisson arrival process. The implications pointed out by Crawford are as follows:

> There are times when removals seem to occur in clusters; and because breaks are likely to occur in clusters we must conclude that maintenance is not a "memoryless" process. But a lack of memory is implied by the assumption in our models that different sorties or different time intervals are independent. Even more troublesome, sometimes we don't have any idea what the clock is, all we know is that something other than sorties or flying hours seems to be driving removals [7:20].

It seems clear that the methods the Air Force uses to forecast spare parts requirements makes many assumptions that are probably inaccurate. The resources can be better allocated, if the methods used take into consideration the more complex factors that are present in the actual data. The new computerized data systems, such as the Central Data System for the F-16 and the Automated Maintenance Systen for the C-5, are providing better sources of data for analysis

than has been available, so it is becoming possible to take these factors into consideration. Crawford makes the succinct observation that if we want to "...intelligently buy spare parts, even for peacetime, we need to know how much of the variation is manageable and then buy resources to cover the rest (7:20)." He goes on to state how much harder it will be to do this for wartime support, especially when the ramifications of that kind of environment are considered.

TIME SERIES ANALYSIS

This section reviews a time series analysis that was recently completed on USAF C-141 data. The methodologies used in the article reviewed are generally the same as that used for the thesis research,on the F-16 data in Appendix A. Because of the complicated description of time series analysis, detailed methodologies used in these studies will be held over to chapter 3 of this thesis, where examples and graphs will aid in describing these methods, thus making the description more meaningful and avoiding duplication of effort.

USAF Study

In December 1982, Singpurwalla and Talbott (16) used time series analysis to investigate the interrelationships between alert availability and flying hours for the C-141 aircraft of the U.S. Air Force. Their data included a major

change in operating hours which was brought about by the introduction of the Reliability Centered Maintenance (RCM) concept in 1976. Their data was also "contaminated" because of anomalies in the reporting procedures during the accumulation of the data (16:1). The technique that they used was a combination of transfer function modeling and intervention analysis.

In a previous study, Singpurwalla and Talbott found that the logistics performance of the C-141 fleet was not improved; as a result of RCM they found some deterioration. However, they had some criticism of their study because they did not take some operational variables into consideration, such as flying hours. The study also ignored the fact that the logistics performance variable, alert availability was "messy" (16:2). The article reviewed here was instigated in order to rectify these deficiencies, and to determine if the expected benefits of RCM were an improvement over the previous system used by the Air Force. The expected benefits included reduced scheduled maintenance by extending the maintenance intervals, and therefore an increase in alert availability.

The Box-Jenkins method was used for the transfer function portion of the study. The variables, labeled X and Y, represented the flying hours of the fleet of C-141's and the alert availability of that fleet of aircraft, respectively. The series X was first reduced to a white noise model and then because of the "messy" data for the variable Y, it was

reduced to white noise using an intervention analysis model. The intervention was defined as the point in time when the RCM was introduced into the system, which caused a change in the response of Y to the input sequence (16:4). The process is known as prewhitening the respective time series, which is necessary before a transfer function model can be achieved.

Singpurwalla and Talbott developed an equation for their final transfer function model after they had estimated the coefficients for the variables. The "...nonzero coefficients associated with the X_t's imply that flying hours do have an effect on the alert availability in a manner specified by the functional form of their equation (16:12). They found that there was a reduction in the variability of the flying hours as of the inception of RCM. A concluding comment in the article supports conclusions in some of the articles reviewed earlier. That is, they pointed out that their final equation "...supports the adage that, 'the more you fly, the less you fail,' within limits (16:12)." Another conclusion was that the final model supported the premise that RCM has a tendency to reduce the alert availability.

Use of Time Series Analysis

Throughout this chapter comparisons have been made to the fact that there is a "linearity" issue and that this assumption has caused support problems. Also noted is the fact that demands per flying hour data is collected over

time thereby making time a factor, which has been ignored. Because time is a factor there are interrelationships between the two variables, demand and flying hours. This relationship is not necessarily linear, but time series analysis methods are the only way to find out what the relationship really is. Once this interrelationship is found, a forecast, (which doesn't have to assume a linear relationship), can be made.

CHAPTER 3

METHODOLOGY

This chapter will begin with an overview of time series analysis, followed by detailed descriptions of the implementation of these methods and the data to be analyzed. After the overview the methods used to prewhiten the individual series will be described, then the method for combining the prewhitened models into transfer function models will be described. From the transfer function model a forecasting model can be made. Finally, a transfer function model of one pair of series, using the original data without prewhitening, will be shown to demonstrate the difference time series methods make.

The data used in this research was provided by the data analysis branch of the F-16 SPO, (ASD/YPDF). This data is collected via a contract with Dynamics Research Corporation, through a central data bank which is fed from all F-16 bases in the Air Force.

Time Series Analysis - Overview

This section will give an overview of the Box-Jenkins method for the analysis of the data. The method consists of several steps, the first of which is using historical observations of a time series to identify a tentative model. The

second step involves estimating the unknown parameters to the tentatively identified model. The third step tests the adequacy of the tentative model and allows identification of steps to improve it if necessary. When these steps are finished, the resultant model can be used for forecasting.

Identification of the tentative model, using the historical observations, involves the concepts of autocorrelation, partial autocorrelation, cross correlations between the series (for multivariate series), and finding out if the time series are stationary or non-stationary. Autocorrelation describes the association or mutual dependence between values of the same variable but at different time periods. Partial autocorrelations are analogous to autocorrelations in that they indicate the relationship of the values of a time series to various time lagged values of the same series. However, they differ from autocorrelation in that they are computed for each time lag after removing the effect of all other time lags on the given time lag and on the original series. In essence, they show the relative strength of the relationship that exists for varying time lags (13: 247). Cross correlation is for the multivariate time series what the simple autocorrelation is for the univariate series. They are standardized measures, between -1 and +1, of the association between the present values of a given variable and past, present, and future values of another time series variable. The cross correlations are used to identify the form of the multivariate model (13:587).

The residuals of the time series must also be checked for stationarity. The patterns that the auto and partial correlations produce, along with the pattern of the residuals, indicate the tentative model to be used for estimation of the parameters. This model has the form of:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots + \phi_p X_{t-p} + e_t - \theta_1 e_{t-1} + \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q} \quad \text{(eq. 1)}$$

if it is stationary. The autoregressive portion of the model is represented by the ϕ_i's, the moving average portion is represented by the θ_i's and, the e_i's represent the error for each observation. The subscript p and q represent the order of the model for autoregressive (AR) and moving average (MA) portions of the model, respectively. This is conventional Box-Jenkins notation. An example of the above equation is:

$$X_t = \phi_1 X_{t-1} - \theta_1 e_{t-1} + e_t \quad \text{(eq. 2)}$$

where e denotes the error.

The stationarity can be identified by observing the plot of the residuals of the model, if the residuals fluctuate, centered around the mean, it is stationary. If there is not a constant mean then the model is non-stationary and must be differenced to obtain values that can be described by a stationary process. The first difference takes the form:

$$Z_t = \nabla Y_t = Y_t - Y_{t-1} \qquad \text{for } t = 2,\ldots\ldots,n \qquad \text{(eq. 3)}$$

Generally, the first difference of a series is sufficient to accomplish a stationary condition. The second difference of a series takes the form:

$$Z_t = \nabla^2 Y_t = Y_t - 2Y_{t-1} + Y_{t-2} \quad \text{for } t = 3,\ldots\ldots,n$$

(eq. 4)

Occasionally, it is necessary to take the natural logarithm of a series prior to differencing it, in order to get it to a stationary condition. The computer packages programmed for time series analysis will accomplish all of these calculations.

To identify the tentative model, after making it stationary, one has to look at the autocorrelation function (ACF) pattern in conjunction with the partial autocorrelation (PACF) pattern. These patterns will indicate an autoregressive (AR) or a moving average (MA) process is present. It may be that both are affecting the model, which would become an autoregressive integrated moving average (ARIMA) model. The integrated portion (I) is the level of differencing required to make the series stationary, it is denoted by a d. The order of p and q is identified by the pattern plotted in the PACF. In general, an AR model will have an exponentially decreasing pattern or an decreasing sine wave pattern in the ACF plot. The PACF will show a spike for each order of the model. On the other hand, an MA model will show a spike and then the pattern will drop off sharply in the ACF. The number of spikes will approximate the order of the model. The PACF for the MA will show an exponentially decreasing pattern or a decreasing sine wave pattern. The order of the model, (p,d,q), is given the number which corresponds to the number of spikes identified in the ACF and PACF

and the level of difference used.

Once the tentative model is identified, the values of the coefficients, ϕ_i and θ_i, must be estimated. This can be done by hand but is very difficult for a large time series. The computer is programmed to do this estimation and will go through an iterative process until it gets the value of the mean squared error (MSE) cannot be decreased further. At this time the final estimate for the model is specified using the parameters found for ϕ_i and θ_i. For example, using the general equation for an ARIMA (1,Ø,1) model (see eq. 2), if the coefficients are .3Ø and .45 respectively, the model becomes:

$$X_t = .30X_{t-1} - .45e_{t-1} + e_t \qquad \text{(eq. 5)}$$

The test of the adequacy of the model is the next step. This test is simply checking to see that residual differences between the time series and those estimated by the model are white noise. The errors are represented by the equation:

$$e_t = X_t = \hat{X}_t \qquad \text{(eq. 6)}$$

The autocorrelation coefficient of the residuals, e_t, can then be found. This will show up as a pattern in the residuals, which is then interpreted. If none of the autocorrelations are significantly different than zero, the errors are assumed to be random, the residuals are white noise, and the model is adequate. If the errors are not random then the model is still not adequate and the above process, beginning with the identification of a tentative model, must be repeated until the final model is all white noise (11:251).

All forecasting methods assume some pattern or relationship exists that can be identified and used as the basis for preparing the forecast. In order to identify that pattern, the data must be analyzed, beginning with the historical observations as they were recorded over time. The actual flying hours for each month are assigned the independent variable "X" and the dependent variable, "Y", represents the demands or removals per month. The variable X_t, X_{t-1}, would represent the observed value of actual flying hours at the last or latest observation and the observation just previous to that. The data used in this thesis has 47 observations over a 47 month time frame beginning with June 1979 inclusive through April 1983, so the variable X_{t-47} would represent the observed value for June 1979. A variable X_{t+5} represents a forecast five periods or months ahead.

With a transfer function the dependent series, Y_t, can be represented by a linear operation on the independent series, X_t, plus a noise component n_t when Y_t, X_t, and n_t are all stationary (18:15). The X_t and Y_t series, used in the transfer function, are prewhitened from the original series.

Prewhitening the Univariate Series

The data was analyzed with the TIMES software program (20). This program is resident on both the Cyber and the Harris/500 computers at AFIT.

Before the transfer function model can be used, each individual series must be prewhitened. An identity function

run was made for each univariate series so that a starting tentative model could be identified. The series of actual flying hours provides an illustration of the method to identify and prewhiten a univariate series in preparation for inclusion in the transfer function model. Figure 1 is the observed series for the actual flying hours, it shows that the data is not stationary because of the unequal deviations about the mean. This non-stationarity must be removed before a model can be applied. Figure 2 illustrates the scatterplot of the residuals after a first order difference has been done. The model is now stationary, so the ACF and PACF will provide a proper graph to use in determining a tentative model. The autocorrelation function (ACF), Figure 3 , and the partial autocorrelation function (PACF), Figure 4, are examined to determine the order of the model. An autoregressive integrated moving average (ARIMA) model is specified which will remove all the correlation within the variables and leave only random noise for the prewhitened models. The residuals from this prewhitened series provide the input to the transfer function model.

Figure 1

Deviations from the Mean - Non-stationary

Scatterplot of the unaltered series (actual flying hours). The zero line with the MMM's represents the mean of the series. The plot shows how the series deviates from the mean.

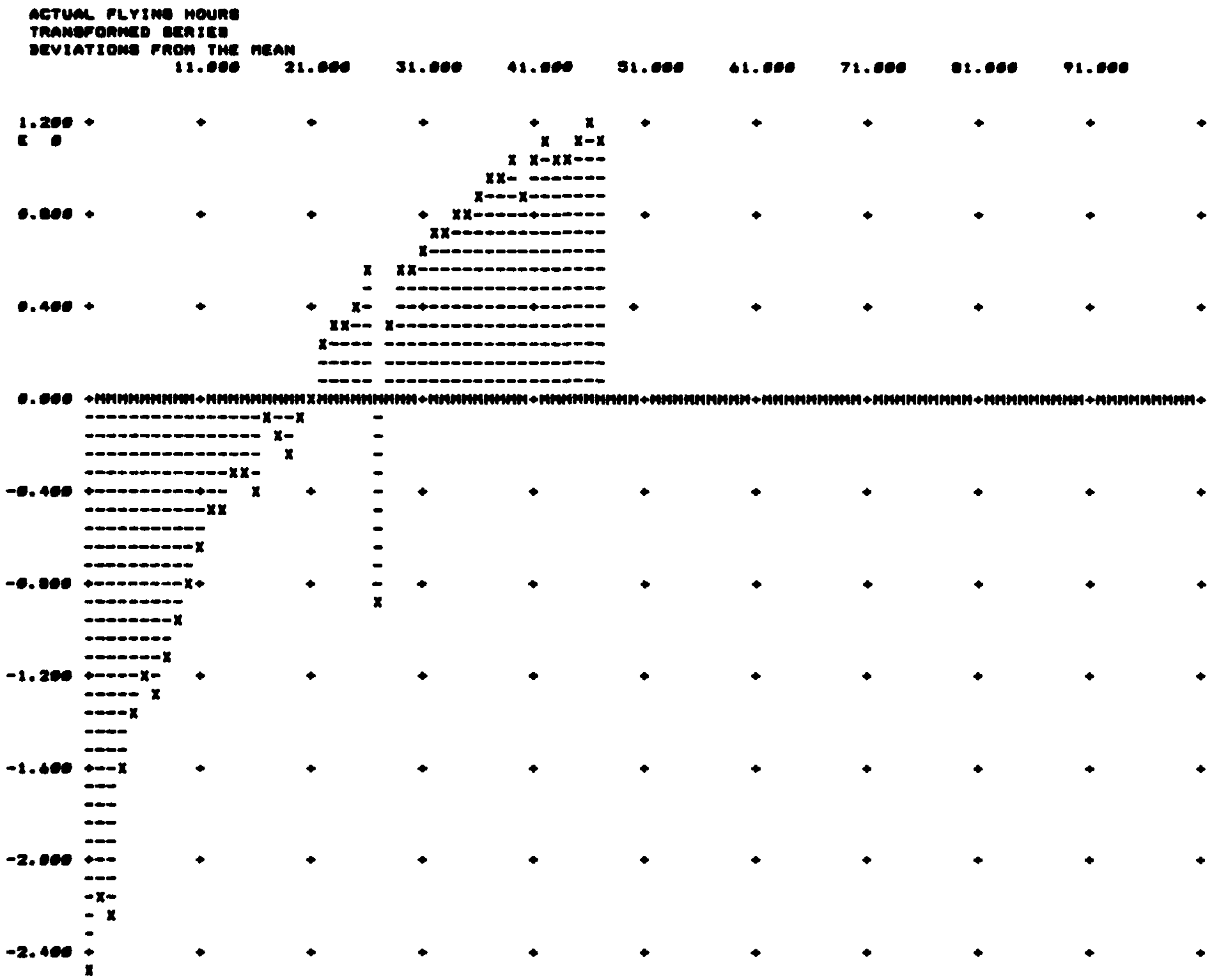


Figure 2

Deviations from the Mean - Stationary

Scatterplot of the residuals after first order differencing. The residuals are now stationary about the mean.

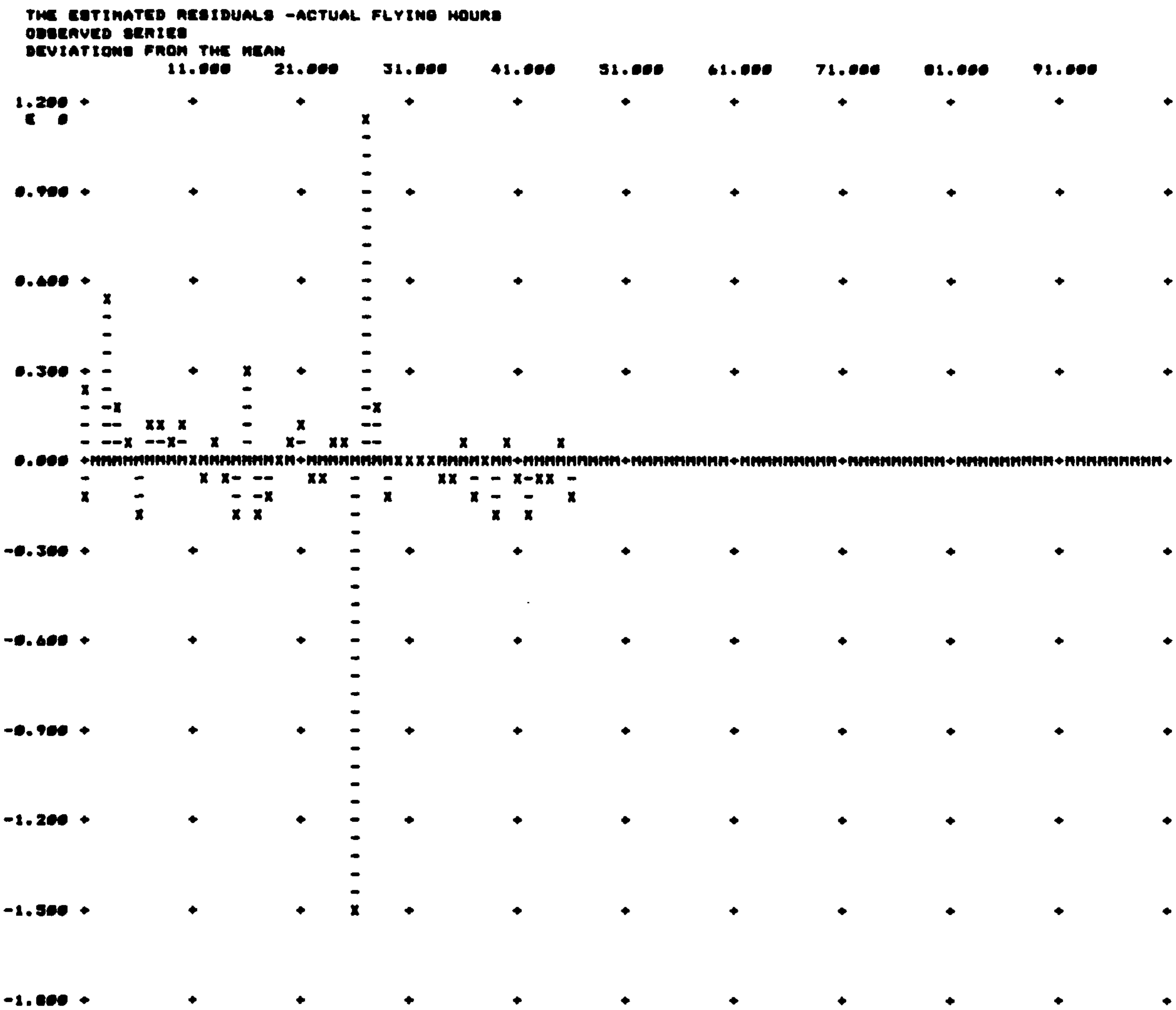


Figure 3

Autocorrelation Function

The negative spike at lag 1 is significant because it is greater than two standard deviations (+/-.300).

```
DATA - THE ESTIMATED RESIDUALS - ACTUAL FLYING HOURS                                     46 OBSERVATIONS

DIFFERENCING - ORIGINAL SERIES IS YOUR DATA.

DIFFERENCES BELOW ARE OF ORDER   1

ORIGINAL SERIES
MEAN OF THE SERIES =0.70395E-01
ST. DEV. OF SERIES =0.31711E+00
NUMBER OF OBSERVATIONS =   46

 1- 15   -0.39  -0.00  0.09  0.02 -0.04  0.03  0.01  0.07  0.06 -0.20  0.16 -0.07  0.07 -0.05 -0.03
 ST.E.    0.15   0.17  0.17  0.17  0.17  0.17  0.17  0.17  0.17  0.17  0.18  0.18  0.18  0.18  0.18

MEAN DIVIDED BY ST. ERROR = 0.16767E+01

TO TEST WHETHER THIS SERIES IS WHITE NOISE, THE VALUE  0.11855E+02
SHOULD BE COMPARED WITH A CHI-SQUARE VARIABLE WITH  15 DEGREES OF FREEDOM

THE ESTIMATED RESIDUALS
GRAPH OF OBSERVED SERIES ACF
```

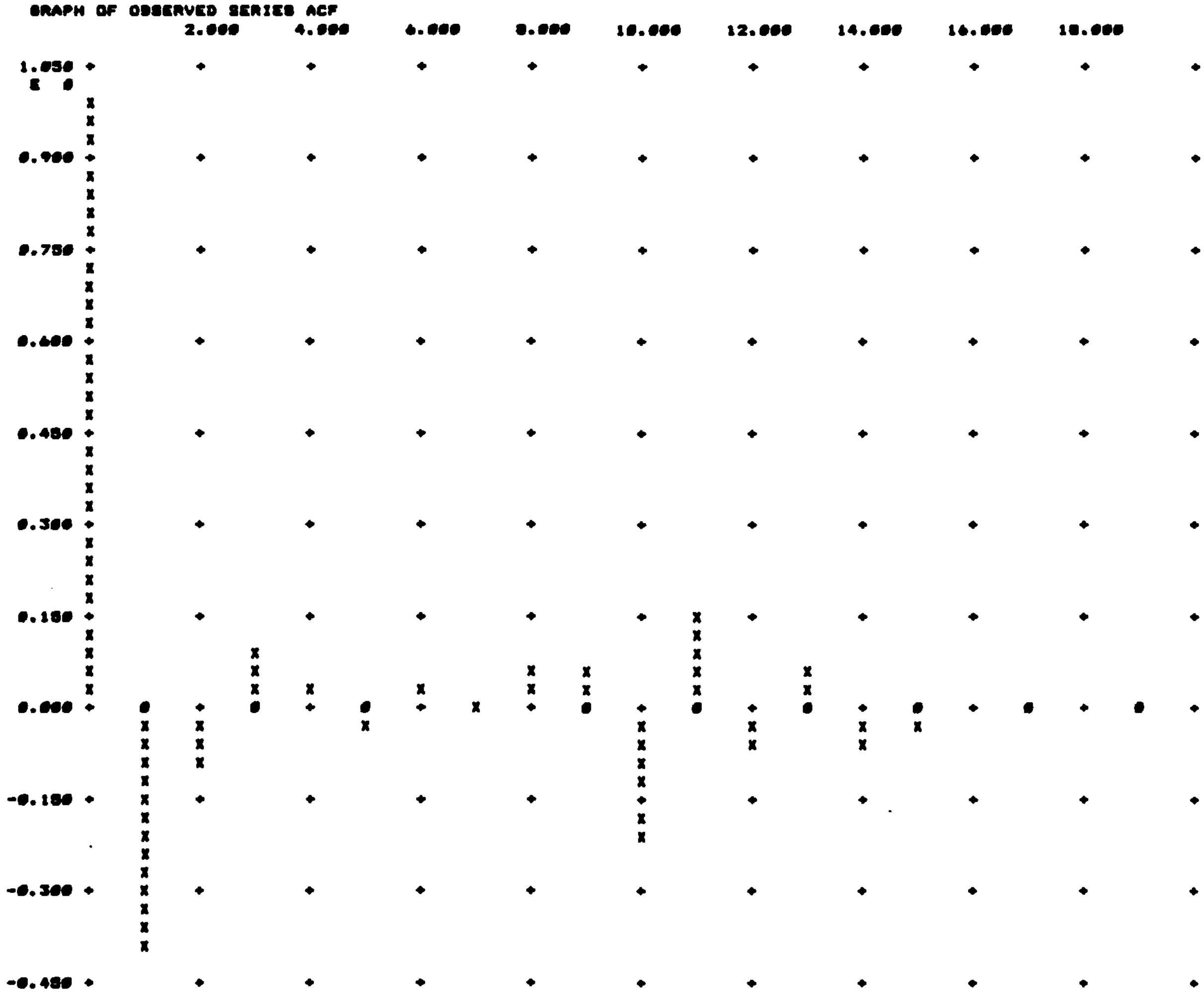


Figure 4

Partial Autocorrelation Function

The autocorrelation function and this partial autocorrelation function have significant spikes which are used to determine the tentative model.

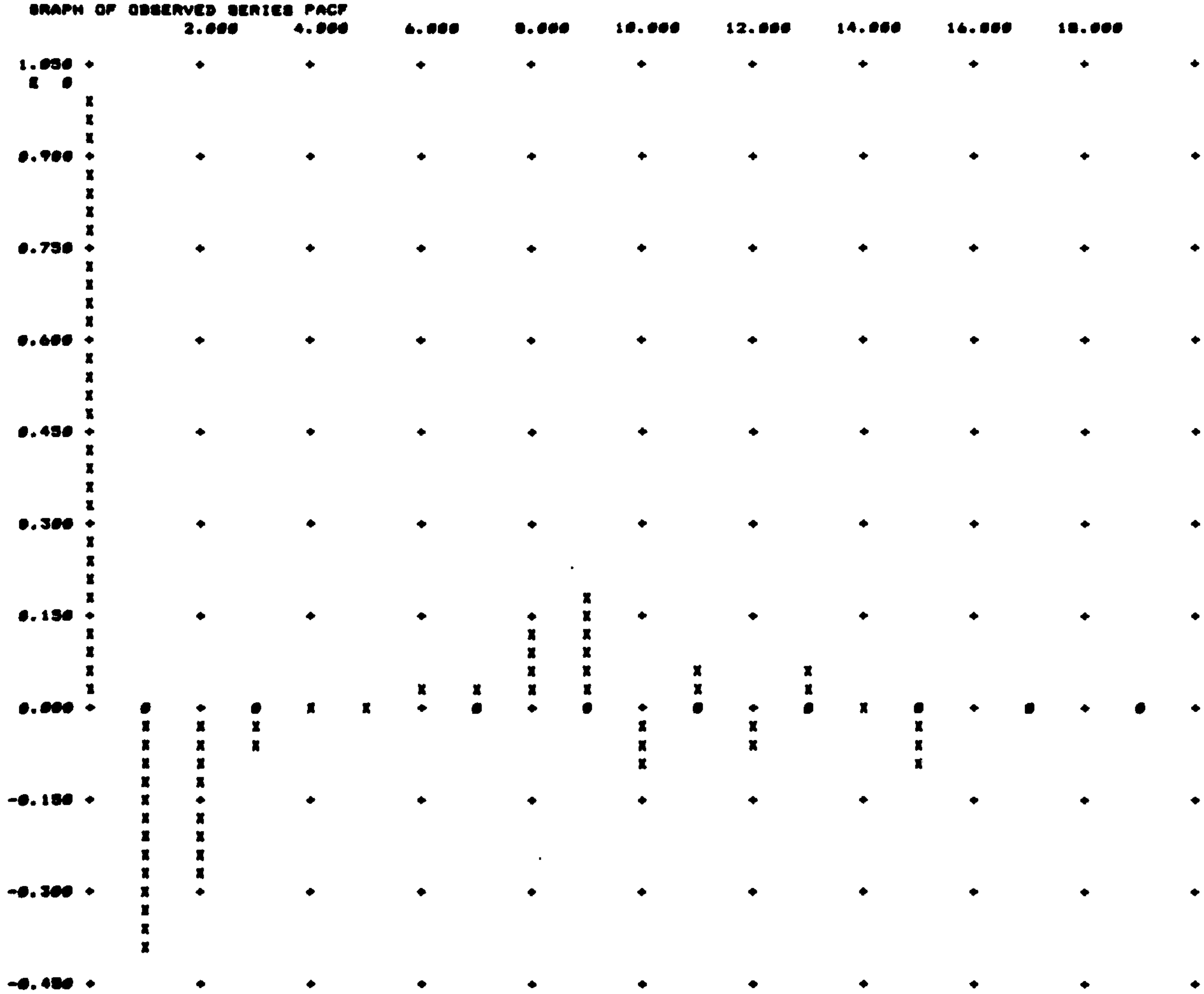
PARTIAL AUTOCORRELATIONS

DATA - THE ESTIMATED RESIDUALS - ACTUAL FLYING HOURS 46 OBSERVATIONS

DIFFERENCING - ORIGINAL SERIES IS YOUR DATA.

DIFFERENCES BELOW ARE OF ORDER 1

THE ESTIMATED RESIDUALS
GRAPH OF OBSERVED SERIES PACF



The original graphs of the ACF and the PACF indicated that the tentative model should be an auto regressive order one. The patterns of the series after differencing (charts 3 and 4) have significant spikes at lag 1 in the ACF and lags 1 and 2 in the PACF. A significant spike is one that extends beyond two standard deviations (in this case beyond +.300 and -.300). The two spikes in the PACF are indicative of an order 2 model. The pattern in the ACF also shows a dampening sinusoidal pattern further indicating an AR function. The process of identifying a final model is an iterative one, in this case an ARIMA (2,1,0), as is indicated in the printout of the identification run, is the most probable model to start with. An ARIMA (2,1,0) model is an AR order 2 with a difference of order 1 and no MA function.

When the correct, most parsimonious, model is found the residual mean square will be at the smallest possible value. Also the Chi Square value shown in Figure 3 will be used to verify that the model is white noise. The residual mean square for the identification model with the first difference taken to make the series stationary is found in Figure 5. It should also be noted that the data was transformed with a logarithmic function. This was done because the data for the actual flying hours are very large numbers, compared to the demand data.

Figure 6 is a power spectrum of the actual flying hour residuals after taking a first difference. From this graph,

seasonality and the fit of the data can be determined. Ideally, the power spectrum of the residuals should be as flat as possible, that is, a horizontal line drawn through the spectrum should be centered on the SSS's, thereby indicating that the residuals are white noise.

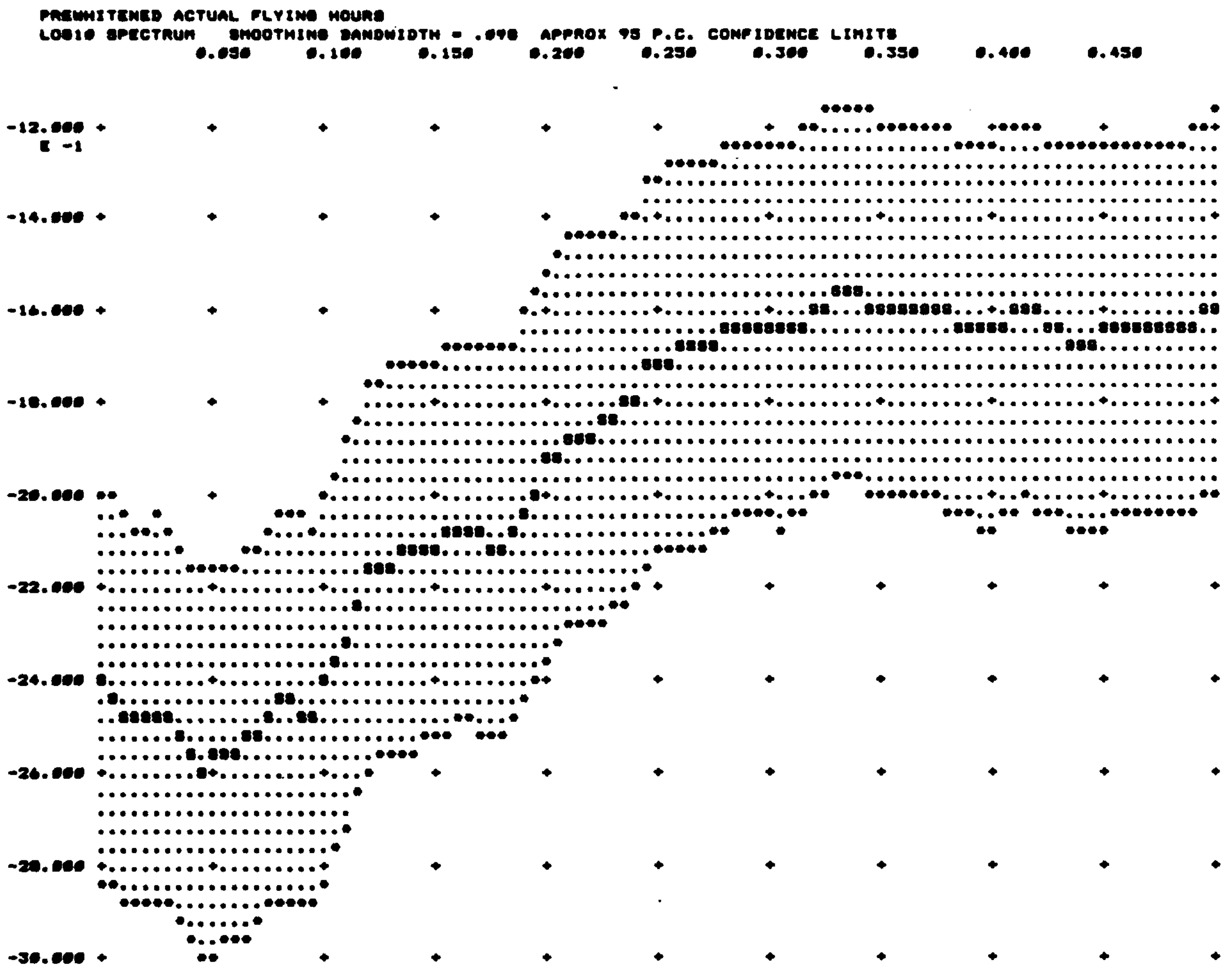
Figure 5

Summary of Model

```
****************************************************************************************************

DATA - Z = ACTUAL FLYING HOURS                                                       47 OBSERVATIONS

DIFFERENCING ON Z - 1 OF ORDER  1

MODEL DEVELOPED WITH TRANSFORMED DATA = LOG(Z(T)+0.00000E+01)

****************************************************************************************************

PARAMETER          PARAMETER          PARAMETER          ESTIMATED                95 PER CENT
 NUMBER              TYPE               ORDER              VALUE         LOWER LIMIT        UPPER LIMIT

****************************************************************************************************

NO PARAMETERS IN MODEL

****************************************************************************************************

OTHER INFORMATION AND RESULTS

****************************************************************************************************

RESIDUAL SUM OF SQUARES      0.48080E+01      46 D.F.            RESIDUAL MEAN SQUARE       0.10452E+00

NUMBER OF RESIDUALS              46                               RESIDUAL STANDARD ERROR    0.32330E+00
```

Figure 6

Power Spectrum



The Final Prewhitened Univariate Model

The final model for the actual flying hours is an ARIMA (2,1,2). This model can be represented by the equation:

$$(1-\phi_1 B-\phi_2 B^2)(1-B)Z_t = (1-\theta_1 B-\theta_2 B^2)a_t \qquad \text{(eq. 7)}$$

The backshift operator, B, is a Box-Jenkins notation that is used to simplify the writing of an equation. In the above equation the backshift operator B^2 is the equivalent of Z_{t-2} and the random error is represented by a_t. The d^{th} difference of Z_t is represented by $(1-B)^d Z_t$.

Figure 7 is a periodogram of the ARIMA (2,1,2) model. This represents the "fit" of the series, a perfect fit would follow a diagonal line through the center of the graph. This fit is as close as possible with the number of observations available. It should be noted here that as more observations are accumulated it may be possible to improve this model of the actual flying hours time series.

Figures 8 and 9 are the ACF and PACF functions of the ARIMA (2,1,2) model. The spikes that were present in the identification model are now gone and all lags are within the two standard deviations. Note that one standard error can be found in Figure 8, it is printed out for each lag and listed in the row labeled ST.E. Two standard deviations are needed to determine if the pattern is white noise, these are found by either multiplying the figure given in the ST. E. or by Bartlett's approximation. Bartlett's approximation for two standard errors is equal to 2 times the square root of the reciprocal of the number of observations (17).

The Chi-Squared test is used to test whether the mean values of the autocorrelations is significantly different than zero. If the value of the Chi-Square test is smaller than the corresponding value from a table of computed Chi-Square values, then the data are random, without any pattern (13:583). Figure 8 gives a computed Chi-Squared value of 6.0612 with 11 degrees of freedom, this is compared with a tabled value of 17.2750 at $X^2_{.100}$. Thus the data are not autocorrelated.

Figure 7

Best Fit Periodogram of Actual Flying Hours

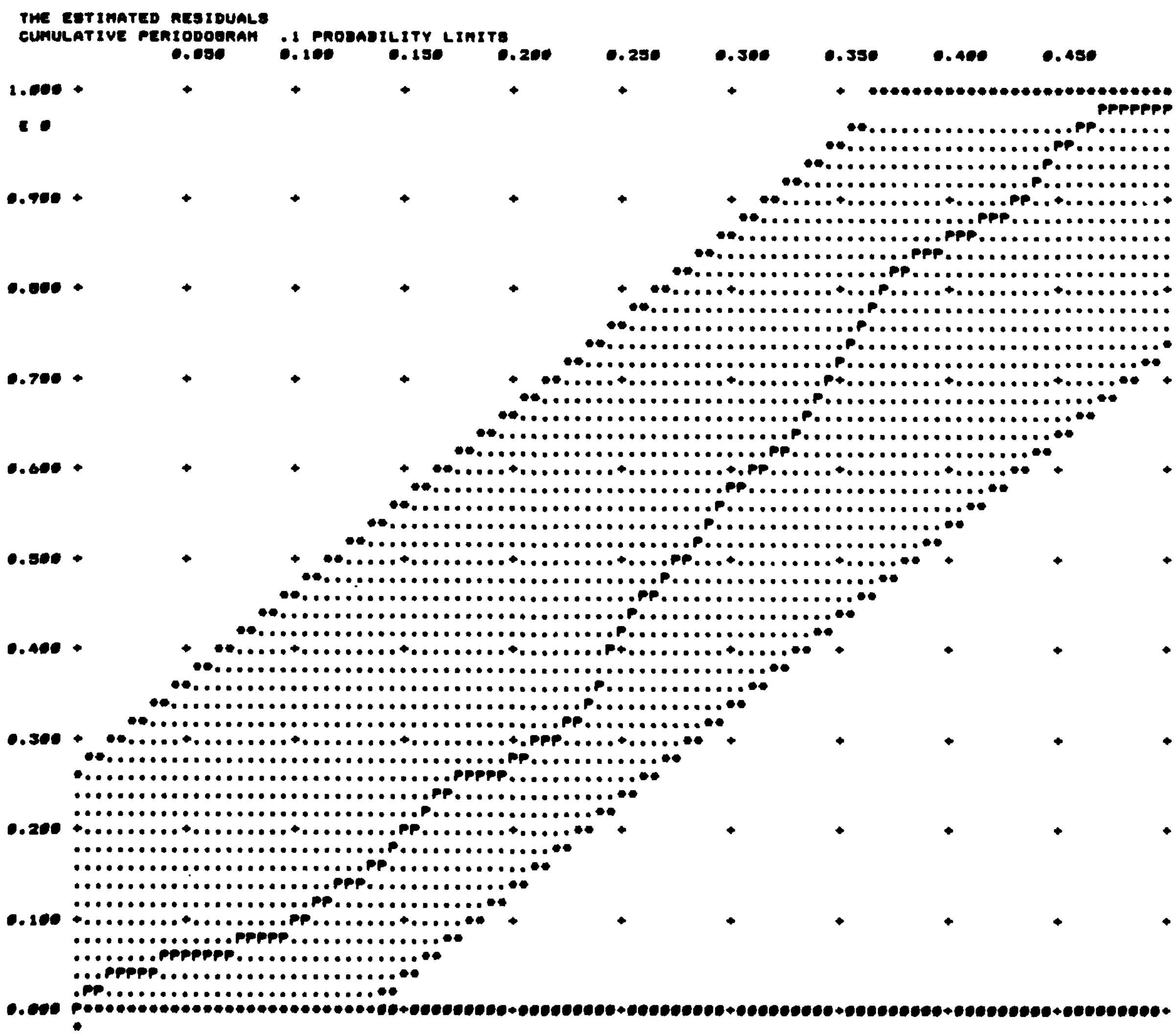


Figure 8

Autocorrelation Function of ARIMA (2,1,2) Model

```
DATA - THE ESTIMATED RESIDUALS - ACTUAL FLYING HOURS                    44 OBSERVATIONS

DIFFERENCING - ORIGINAL SERIES IS YOUR DATA.

DIFFERENCES BELOW ARE OF ORDER   1

ORIGINAL SERIES
MEAN OF THE SERIES =0.11332E+00
ST. DEV. OF SERIES =0.26034E+00
NUMBER OF OBSERVATIONS =   44

        1- 15   -0.07 -0.19  0.10 -0.01  0.01  0.03  0.07  0.10  0.04 -0.20  0.13 -0.03  0.05 -0.06 -0.06
        ST.E.    0.15  0.15  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.17  0.17  0.17  0.17  0.17

MEAN DIVIDED BY ST. ERROR = 0.28874E+01

TO TEST WHETHER THIS SERIES IS WHITE NOISE, THE VALUE  0.60612E+01
SHOULD BE COMPARED WITH A CHI-SQUARE VARIABLE WITH  11 DEGREES OF FREEDOM

GRAPH OF OBSERVED SERIES ACF
```

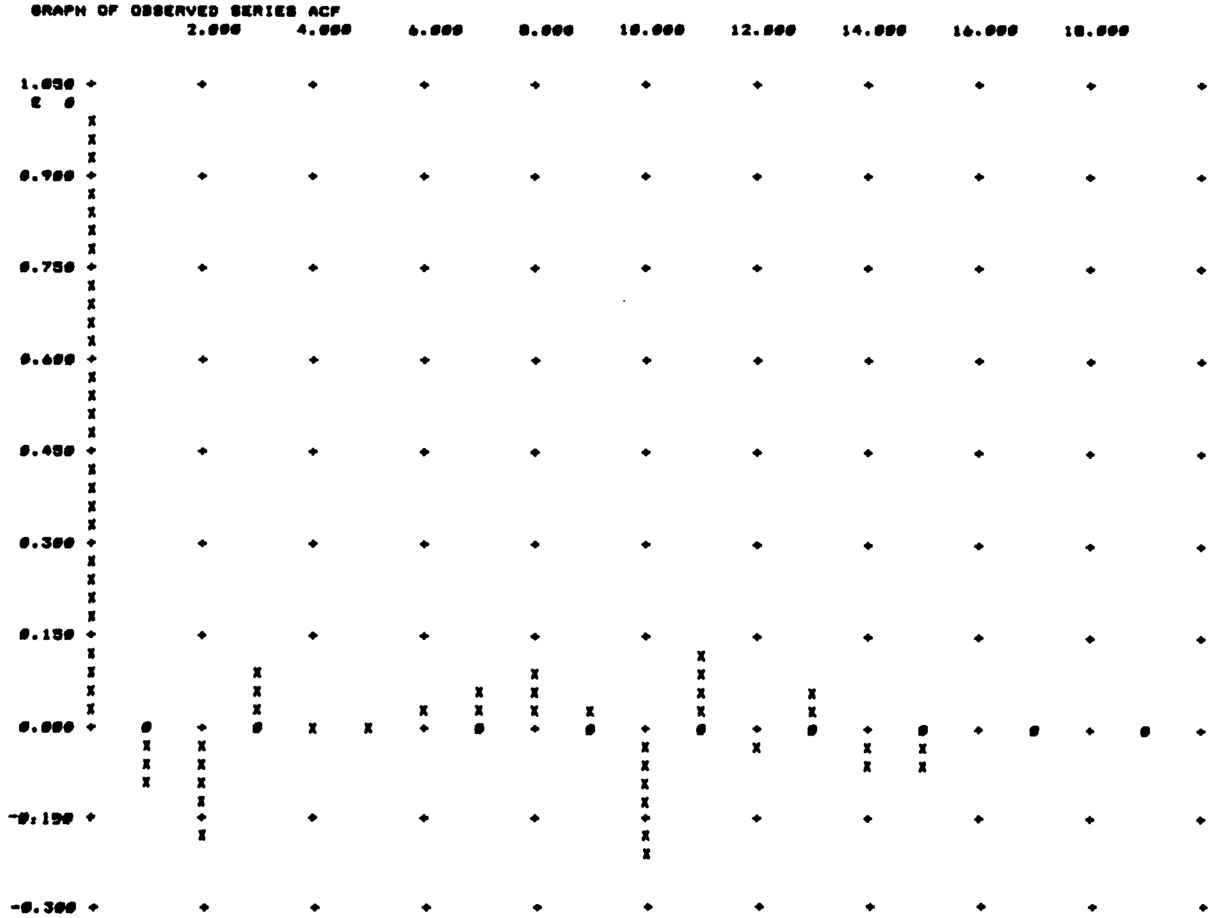


Figure 9

Partial Autocorrelations of ARIMA (2,1,2) Model

DATA - THE ESTIMATED RESIDUALS - ACTUAL FLYING HOURS 44 OBSERVATIONS

DIFFERENCING - ORIGINAL SERIES IS YOUR DATA.

DIFFERENCES BELOW ARE OF ORDER 1

THE ESTIMATED RESIDUALS
GRAPH OF OBSERVED SERIES PACF

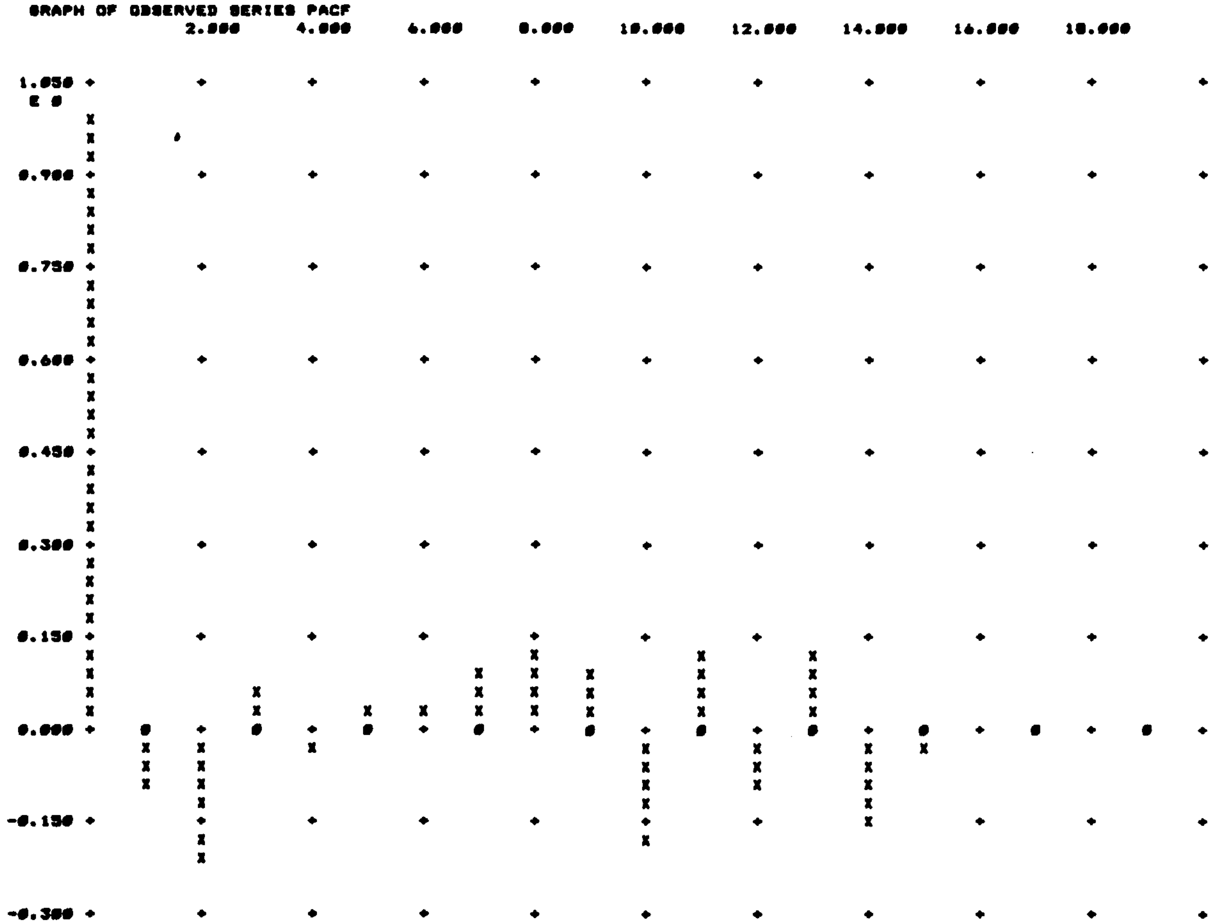


Figure 10 is a summary of the final model for the actual flying hours. This model will be used in the transfer function models where it is combined with the other univariate models to find the cross correlation, or "between" correlation, so that a forecast can be accomplished. Note that the data was transformed with a logarithmic function. The purpose of this is to reduce the magnitude of the monthly observations, thus, making the residuals smaller in their magnitude. This must be done in order to find the impulse response weights during the identity of the transfer function. The impulse response is a series of weights in a multivariate (ARIMA) model relating the independent, input, series to the dependent, output, series. The value of each weight determines the relative importance of each residual to the others, a large weight will cause an impulse in the pattern of the residuals. This pattern, and the weights are usefull in identifying the model. The following section will give more detail on this process.

The first part of Figure 10 is where the information about the coefficients of the AR and MA parameters are given. By inserting this information into equation 7, the final model for the actual flying hours becomes:

$$(1 + 1.0122B - .0084937B^2)(1 - B)Z_t = (1 + .78672B - .43365B^2)a_t$$

The residual mean square for this model is .0086986, which was the smallest found in the iterative process in

developing the model. Finally, the power spectrum of the residuals is indicative of white noise. As noted earlier, this spectrum ideally should have even distribution of the SSS's about a horizontal line drawn through the graph. The distribution in this case is satisfactory and represents the best possible fit of the model to the data. A line drawn at approximately the -2.000 level will have an equal distribution above and below it.

Appendix B contains summary printouts for the balance of the univariate models. These are arranged in the same order as the work unit codes (WUC's) in Appendix A. Equations for each of the five WUC's and the corresponding ARIMA model are:

WUC:42GB0 ARIMA (0,1,1)

$$(1 - 0)(1 - B)Z_t = (1 - .53800B)a_t$$

WUC:14FB0 ARIMA (2,1,1)

$$(1 + .0068762B + .47673B^2)(1 - B)Z_t = (1 - .75544B)a_t$$

WUC:24EBA ARIMA (2,1,1)

$$(1 +.12117B + .31575b^2)(1 - B)Z_t = (1 - .52364B)a_t$$

WUC:46AF0 ARIMA (2,1,1)

$$(1 + .10442B + .38446B^2)(1 - B)Z_t = (1 - .76877B)a_t$$

WUC:46AN0 ARIMA (2,1,0)

$$(1 + .70241B + .28100B^2)(1 - B)Z_t = (1 - 0)a_t$$

The fit of the individual univariate models can be seen in the power spectrum for each model.

Figure 10

Summary of Actual Flying Hours Model - ARIMA (2,1,2)

SUMMARY OF MODEL

DATA - Z = ACTUAL FLYING HOURS — 47 OBSERVATIONS

DIFFERENCING ON Z - 1 OF ORDER 1

MODEL DEVELOPED WITH TRANSFORMED DATA = LOG(Z(T)+0.00000E+01)

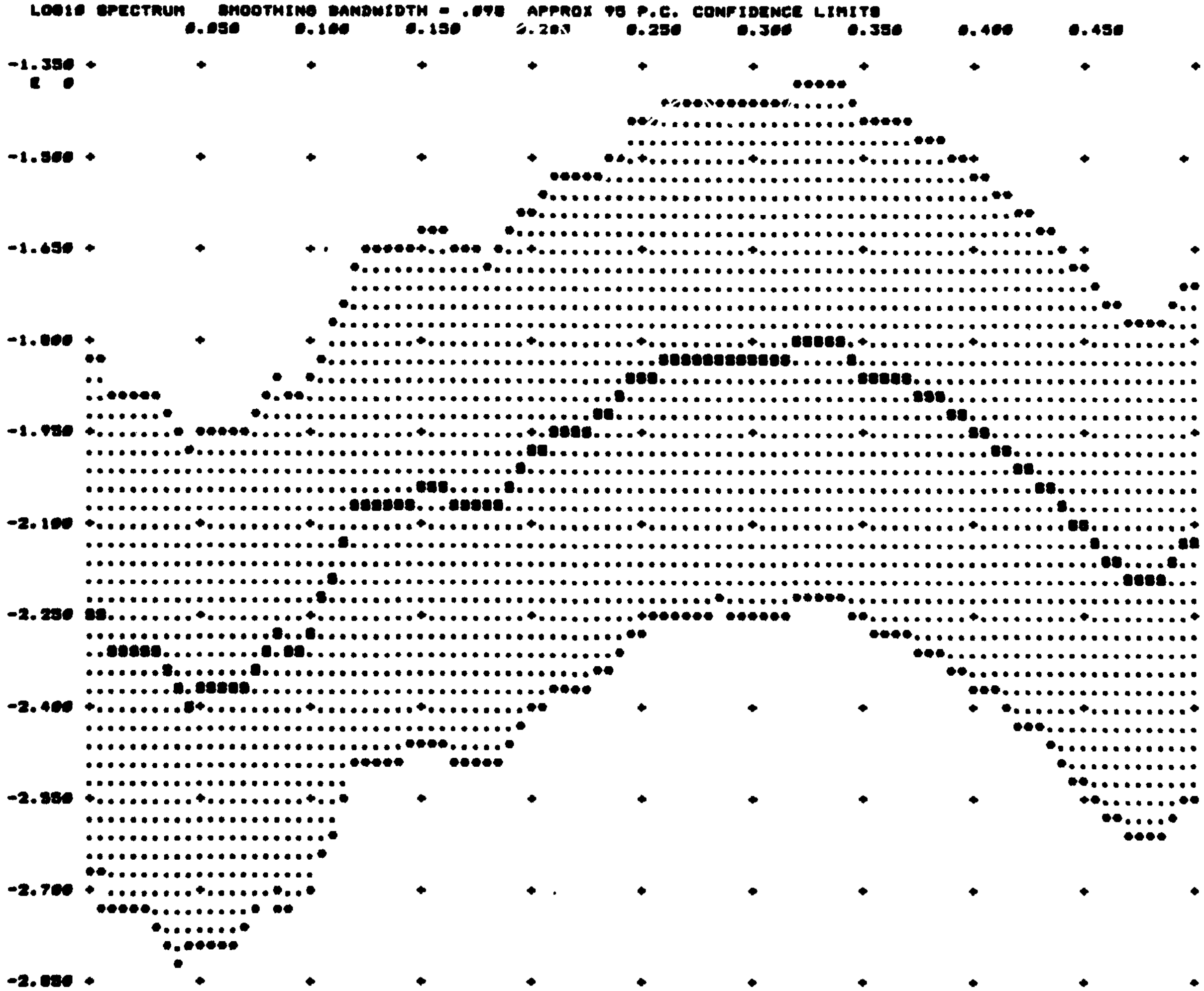
PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	AUTOREGRESSIVE 1	1	-.10122E+01	-.14429E+01	-.58146E+00
2	AUTOREGRESSIVE 1	2	0.84937E-02	-.34880E+00	0.36579E+00
3	MOVING AVERAGE 1	1	-.78672E+00	-.10302E+01	-.54330E+00
4	MOVING AVERAGE 1	2	0.43365E+00	-.11035E+00	0.97764E+00

OTHER INFORMATION AND RESULTS

RESIDUAL SUM OF SQUARES	0.34794E+01	40 D.F.	RESIDUAL MEAN SQUARE	0.86986E-01
NUMBER OF RESIDUALS	44		RESIDUAL STANDARD ERROR	0.29493E+00

PREWHITENED ACTUAL FLYING HOURS

LOG10 SPECTRUM SMOOTHING BANDWIDTH = .098 APPROX 95 P.C. CONFIDENCE LIMITS



The Multivariate Model

The first step, after the prewhitening of each univariate series, is to identify the class of model for the transfer function. The pairs of time series models have been differenced and made stationary. The output series, Y_t (the demands) and the input series, X_t (the actual flying hours), are now represented by the equation;

$$Y_t = (v_0+v_1B^1+v_2B^2+...)X_t+e_t \qquad \text{(eq. 8)}$$

where Y_t is described as the weighted sum of lagged values from both the input and output series plus random error (15: 379). The impulse response weights, v_i's, are difficult to estimate and therefore, the above equation is not an efficient parameterization (15:380).

> According to Box and Jenkins, the model formulation lacks "parsimony." The number of parameter estimates could result in an unstable estimation problem [15:379].

A more general and parsimonious equation for the transfer function is:

$$(1-\delta_1B-...-\delta_rB^r)Y_t = (\omega_0-\omega_1B-...-\omega_sB^s)X_{t-b}+N_t \qquad \text{(eq. 9)}$$

where r is equivalent to the number of cogent past Y_t values, s is equivalent to the number of past X_t values, b is the lag factor (the number of periods until the effect of a change in X_t affects Y_t), and N_t represents the noise factor. The Y_t is the same as found in eq. 8. This model is referred to as an (r,s,b) model.

The impulse response weights, v_i's, are used to provide guidelines to the identification of the appropriate values of the (r,s,b) model. Box and Jenkins demonstrate that the

impulse response weight v_k is simply lag k cross-correlation of the α_t and β_t series, $\rho_{\alpha\beta}(k)$, multiplied by a scale factor (6: 380). The α_t and β_t series are the prewhitened input and output series, respectively. The equation for finding v_k is:

$$v_k = \rho_{\alpha\beta}(k)\,\frac{\sigma_\beta}{\sigma_\alpha} \quad k=0,1,2,\ldots, \qquad \text{(eq. 10)}$$

Equation (10) suggests that the series referred to as "prewhitened" retain information on (Y_t, X_t) interrelationships without the sometimes confounding information on intrarelationships in the individual series. Prewhitening removes the latter information to illuminate the former [15:382].

The impulse response weights, v_k, will have groupings which give clues to identify the correct values for (r,s,b). The quotations below relate to eq. 8 & 9 above.

The clue for b is:
for k = 0,1,...,b-1, the right side coefficient of B^k is 0. Thus, $v_0=v_1=\ldots=v_{b-1}=0$.

The clue for r is:
for k>b+s, the right side coefficient of B^k is 0. Expansion of the left side then implies that $v_k-\delta_1 v_{k-1}-\ldots-\delta_r v_{k-r}=0$. v_k generated from an equation of this type would illustrate patterned behavior. For r=1, a pattern of exponential decrease would be seen (with v_k alternating in sign if $\delta_1<0$). For r=2, a typical pattern would be that of a damped sine wave, although exponential decrease is also likely. Thus, the value of r can be identified through association of impulse response weight patterns that are exactly equivalent to the autocorrelation patterns associated with the same value of the autoregressive order p in a univariate time series model. An additional aid in identifying r may exist in the visible grouping of r "initial values" or "startup values" for the equation given above. These values will be the v_k that appear in the expression for v_{b+s+1}, i.e., $v_{b+s+1},\ldots,v_{b+s-1}$, v_{b+s}. Often, however, these r startup values will seem to be part of the pattern in the v_k for k>b+s.

The clue for s is:
the pattern referred to in the clue for the identifi-

cation of r begins with the impulse response weight v_{b+s+1}. Establishing the beginning of this pattern establishes the value of b+s+1. Given previous identification of b, one may deduce a most likely value for s.

The Transfer Function Model

The transfer function model to be used for this example is of the WUC:14FBØ. Appendix C contains the remainder of the transfer function models.

The identity run for the model used in this example gives the following data to use in identifying a tentative model. The effective number of observations for cross correlation calculation is 44.

Table 1

Model Information

Mean of Series 1	=	Ø.7586ØE-11
St. Dev. of Series 1	=	Ø.25736E+ØØ
Mean of Series 2	=	Ø.11Ø38E-1Ø
St. Dev. of Series 2	=	Ø.843Ø8E+ØØ

The mean values in Table 1 are used with eq. 9 to estimate the v_k values at each lag. This is accomplished by the TIMES program which saves the effort of calculating manually. Table 2 was extracted from the identity run to show the calculated impulse response weights, v_k. Note that lag 6 is a large negative value, this shows up in the plot in Figure 11.

Table 2.

Estimated Impulse Response Weights v(k).

K	V(K)
Ø	Ø.777
1	-Ø.Ø75
2	Ø.186
3	Ø.11Ø
4	-Ø.Ø35
5	Ø.5Ø1
6	-1.391
7	Ø.617
8	Ø.416

Table 3 is the cross correlation values that are plotted in Figure 11. Series 1 data is plotted on the right side of the graph.

Table 3

Cross Correlations
Series 1 - Prewhitened Actual Flying Hours
Series 2 - Prewhitened WUC:14FBØ E1 Comp Assy

Number of Lags on Series 1	Cross Correlations	Number of Lags on Series 2	Cross Correlations
Ø	Ø.237	Ø	Ø.237
1	-Ø.Ø23	1	-Ø.128
2	Ø.Ø57	2	-Ø.Ø83
3	Ø.Ø33	3	Ø.Ø73
4	-Ø.Ø11	4	Ø.254
5	Ø.153	5	-Ø.18Ø
6	-Ø.425	6	-Ø.Ø46
7	Ø.188	7	Ø.Ø81
8	Ø.127	8	Ø.Ø44

Figure 11 represents the cross correlations between the pair of time series. The right side of this plot, (right of zero), is important in that it is the side that is used to identify the final transfer function model. When the model

is correct this side will have all of its spikes within two standard errors.

Figure 11

Cross Correlation Plot

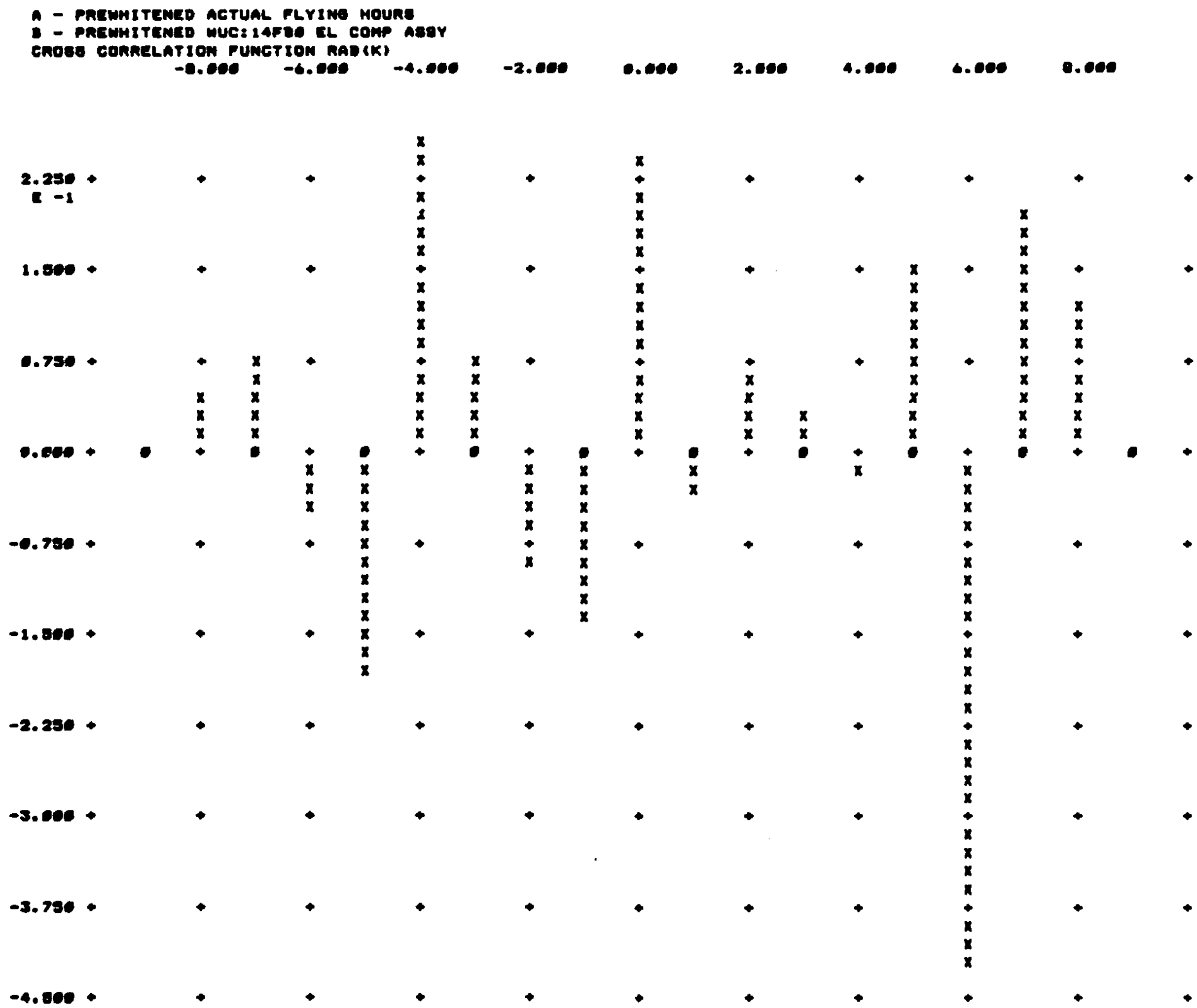


Figure 12 is the estimated impulse response for this model. This figure is a plot of the v_k weights of the estimated cross correlation. With this graphical portrayal and Figure 11 one can estimate the values for r, s, and b. It is obvious that there is not a time lag between the input and output series because of the large spike at lag 0 indicating that v_0 is not equal to zero, therefore, b = 0 for this model. The r value is also zero because there is no apparent pattern in the cross correlation function. The s value is all that remains to figure out. This is easily accomplished by looking at the cross correlation produced by the identity run (Figure 11). The lags that have spikes which are less than two standard errors long have an expected value of zero, therefore, they are not significantly correlated. The lags with spikes longer than two standard deviations are produced by significant inpulse response weights from which the s value can be found. The standard error can be found by taking the square root of the reciprocal of the n observations (6:382).

Figure 12

Estimated Impulse Weights

This figure represents the estimated impulse response that are used to determine the tentative transfer function model

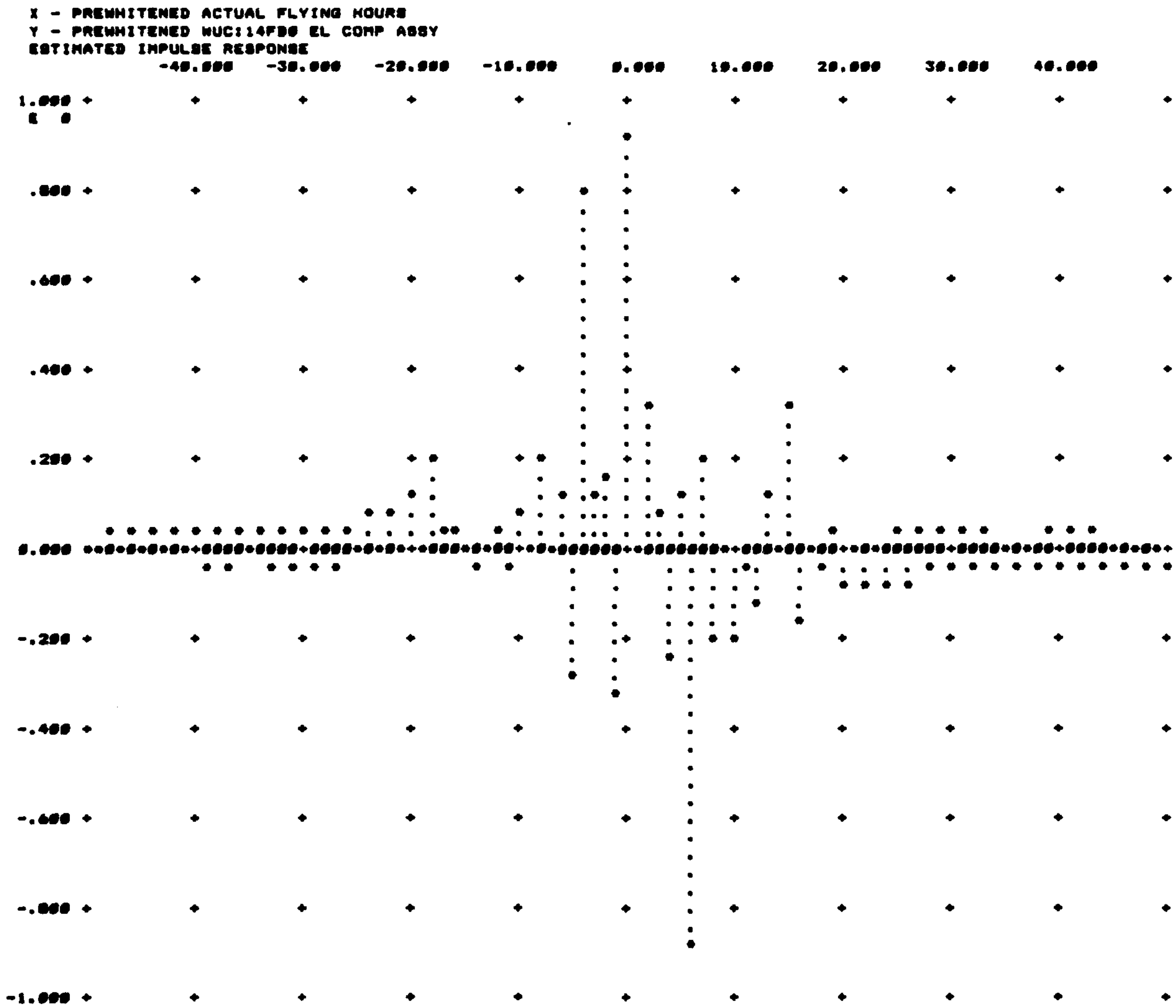


Figure 13 is a summary of the transfer function model. The same type of information as found in the summaries of the univariate models is found here. In addition, the optimum value of b is given, any noise model parameters are given (in this case, since both univariate models were prewhitened, no noise parameters were required). The estimated values for the transfer function parameters are the most important information found in this Figure.

Figure 13

Transfer Function Summary

```
SUMMARY OF MODEL

*******************************************************************************************

DATA - X = ACTUAL FLYING HOURS                                          44 OBSERVATIONS
       Y = WUC:14F00 EL COMP ASSY

DIFFERENCING ON Y - NONE

DIFFERENCING ON X - NONE

*******************************************************************************************

NOISE MODEL PARAMETERS

*******************************************************************************************

PARAMETER      PARAMETER      PARAMETER      ESTIMATED             95 PER CENT
 NUMBER          TYPE           ORDER          VALUE         LOWER LIMIT      UPPER LIMIT

*******************************************************************************************

*******************************************************************************************

TRANSFER FUNCTION PARAMETERS

*******************************************************************************************

    1          INPUT LAG 1        0          .79554E+00     -.16580E+00      .17569E+01

    2          INPUT LAG 1        2         -.16403E+00     -.11496E+01      .82157E+00

    3          INPUT LAG 1        4          .75735E+00     -.25535E+00      .17700E+01

    4          INPUT LAG 1        5          .68720E-01     -.91528E+00      .10527E+01

    5          INPUT LAG 1        6          .17023E+01      .73990E+00      .26647E+01

    6          INPUT LAG 1        7         -.44843E+00     -.13539E+01      .45702E+00

*******************************************************************************************

OPTIMUM VALUE OF B IS  0

*******************************************************************************************

OTHER INFORMATION AND RESULTS

*******************************************************************************************

RESIDUAL SUM OF SQUARES      .16897E+02      31 D.F.      RESIDUAL MEAN SQUARE       .54506E+00

NUMBER OF RESIDUALS                  37                   RESIDUAL STANDARD ERROR    .73828E+00
```

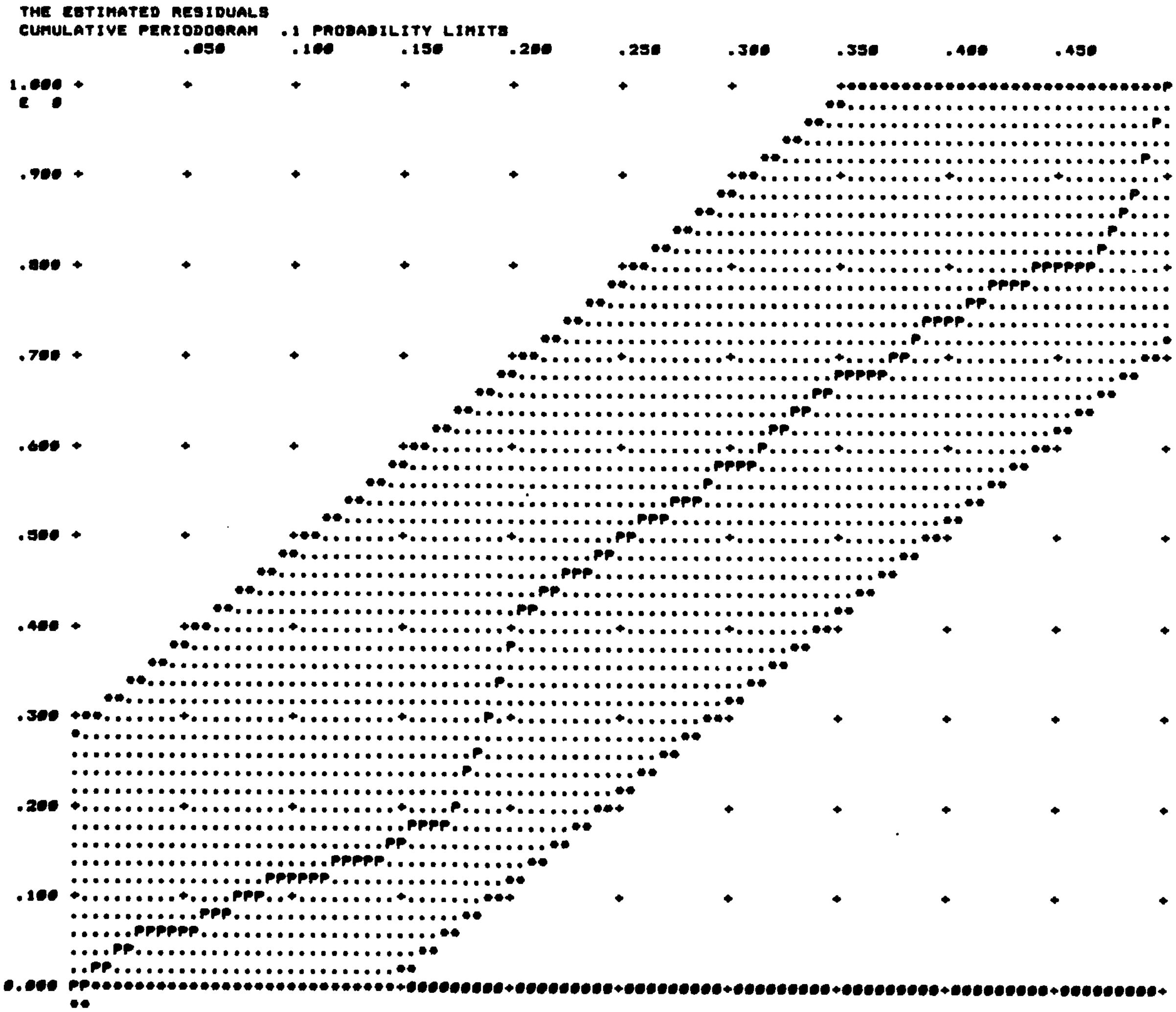
From the data in Figure 13, an equation for the transfer function model can be written by inserting the numbers into eq. 9. The equation for this function is:

$$Y_t = (.79554 + .16430B^2 - .75735B^4 - .068728B^5 - .017023B^6 + .44843B^7)X_t + N_t.$$

The periodogram in Figure 14 represents the fit of the transfer function model within .1 probability limits.

Figure 14

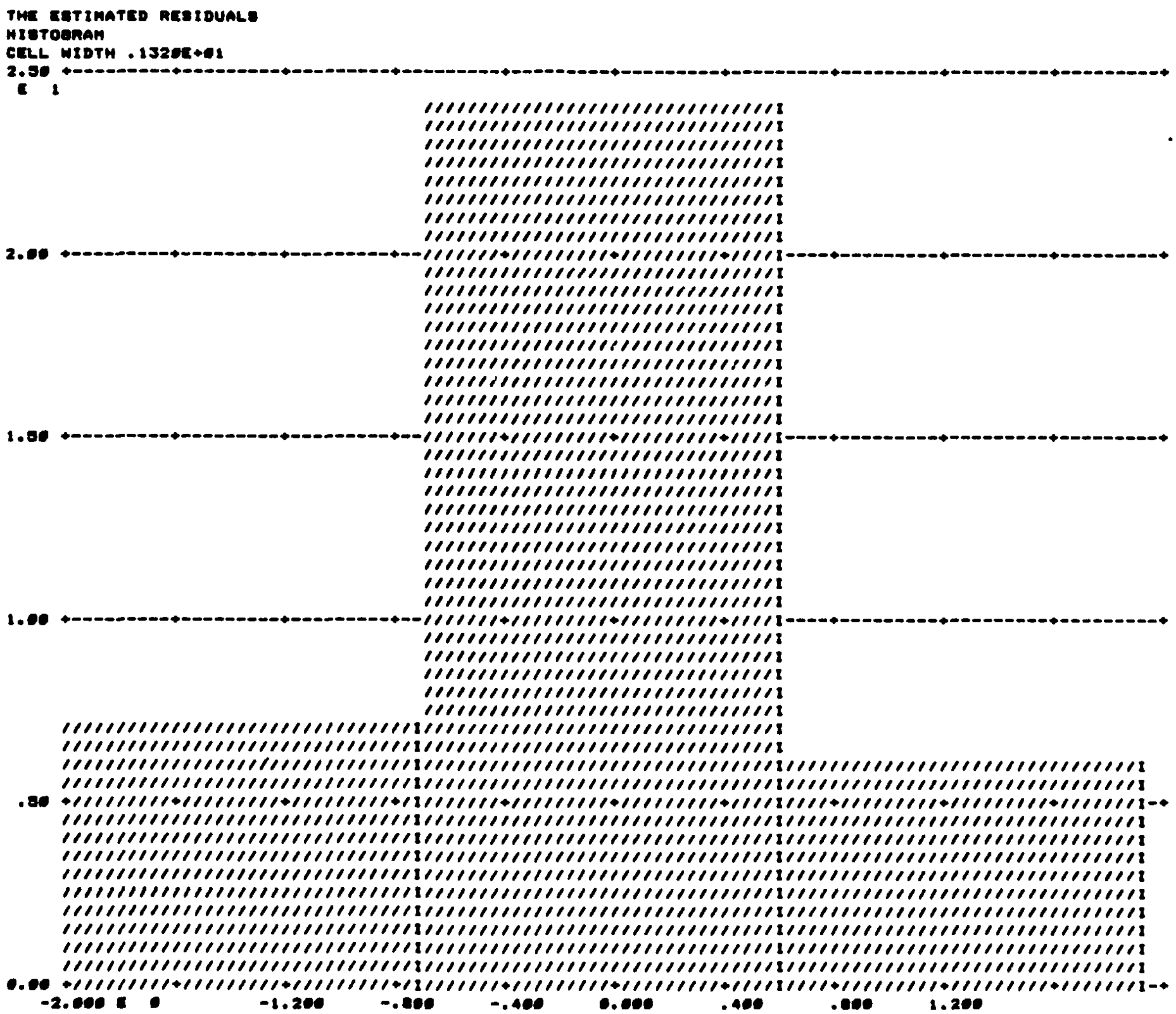
Transfer Function Periodogram



The histogram in Figure 15 represents the distribution of the residuals in the transfer function model. This histogram is a near perfect normal distribution, the histograms for the balance of the transfer function models are found in Appendix C. The others transfer function models do not have as perfect a distribution as this one but they are still well within the expected range of distribution.

Figure 15

Histogram for WUC: 14FBØ Transfer Function.



The cross correlation in Figure 16 shows that none of the lags on the right side have spikes significantly different than zero. This model has all of the between structure correlation removed and is now ready to be used in forecasting. A review of all the cross correlation figures in Appendix C will show that all of the final transfer function models have only white noise on the right side of their cross correlation plots. The equation for Figure 16 has been written above, equations for the balance of the transfer function models, by WUC and type of model are:

WUC:42GB0 (0,8,0)

$$Y_t = (-4.8069 - 3.5346B + 4.9247B^4 - 5.2819B^7 + 1.9522B^8)X_t + N_t.$$

WUC:24EBA (2,4,0)

$$(1 - .077362B + .13579B^2)Y_t = (.79689 - 1.4642B + .88371B^2 - 2.6610B^4)X_t + N_t.$$

WUC:46AF0 (1,6,0)

$$(1 - .35718B)Y_t = (2.3915B - 1.3710B^5 + 1.3305B^6)X_t + N_t.$$

WUC:46AN0 (1,5,0)

$$(1 + .45490B)Y_t = (.52943 - 1.3678B^3 + .61573B^4 - 2.2439B^5)X_t + N_t.$$

Figure 16

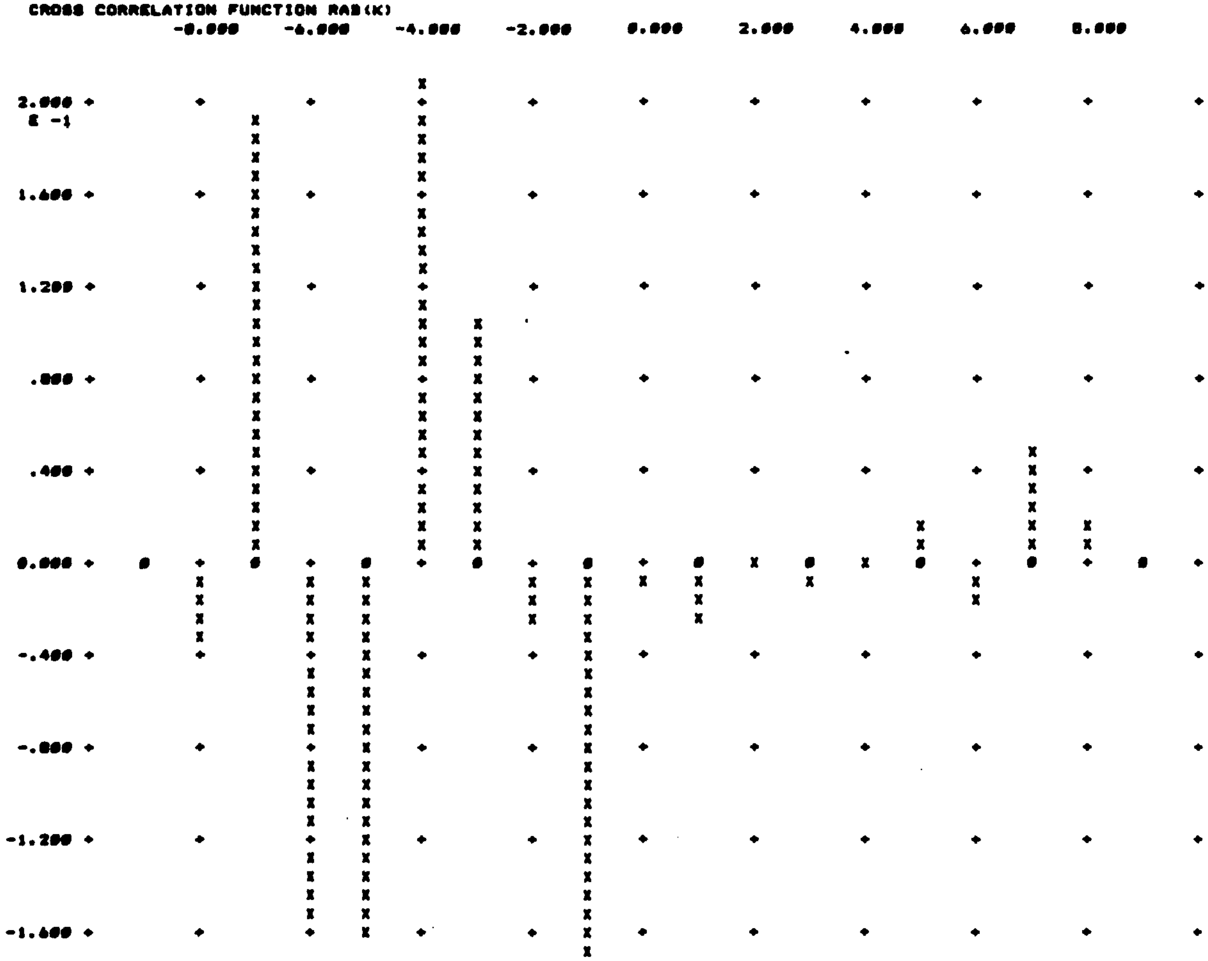
Cross Correlations for WUC:14FB0

SERIES 1 - PREWHITENED ACTUAL FLYING HOURS
SERIES 2 - THE ESTIMATED RESIDUALS

MEAN OF SERIES 1 = -.31356E-01
ST. DEV. OF SERIES 1 = .26075E+00
MEAN OF SERIES 2 = -.60294E-01
ST. DEV. OF SERIES 2 = .67300E+00

NUMBER OF LAGS ON SERIES 1	CROSS CORRELATION	NUMBER OF LAGS ON SERIES 2	CROSS CORRELATION
0	-.011	0	-.011
1	-.020	1	-.160
2	-.000	2	-.025
3	-.011	3	.103
4	-.003	4	.207
5	.012	5	-.157
6	-.012	6	-.153
7	.051	7	.196
8	.019	8	-.033

A - PREWHITENED ACTUAL FLYING HOURS
B - THE ESTIMATED RESIDUALS
CROSS CORRELATION FUNCTION RAB(K)



An Example of a Transfer Function Using Raw Data

The present method of forecasting requirements is to use the linear function, $Y_t = a_0 + a_1 X_t + e_t$. When this type of equation is used, the time factor is ignored, the possibility of seasonal factors is ignored, and it's assumed that the model is adequate. This section will show by comparison, the difference in using raw data, assumed linear, and the time series method of the previous sections. To do this, the data was input to the TIMES program as a transfer function which compares two series of data to determine the between series correlations. In the section on univariate time series it was pointed out that the data was non-stationary and therefore had to be differenced prior to finding a correct model. The same set of time series used in the multivariate section was input, in it's raw form, for this section. This is the form that would be used in the present forecasting methods, i.e., just as it was collected. Compare the figures in this section to those in the previous section to see that the methods of time series analysis do a better job of fitting the data. Figure 17 is a plot of the residuals about the mean (MMM), this plot comes from the run which will be called the 'old method' in the figures and text. Note that it is not stationary, that is, it does not vary uniformly about the mean, but trends across the mean. Compare this plot with Figure 18, which is from the run that produced the figures for the previous section.

Figure 17

Deviations from the Mean
The 'Old Method'

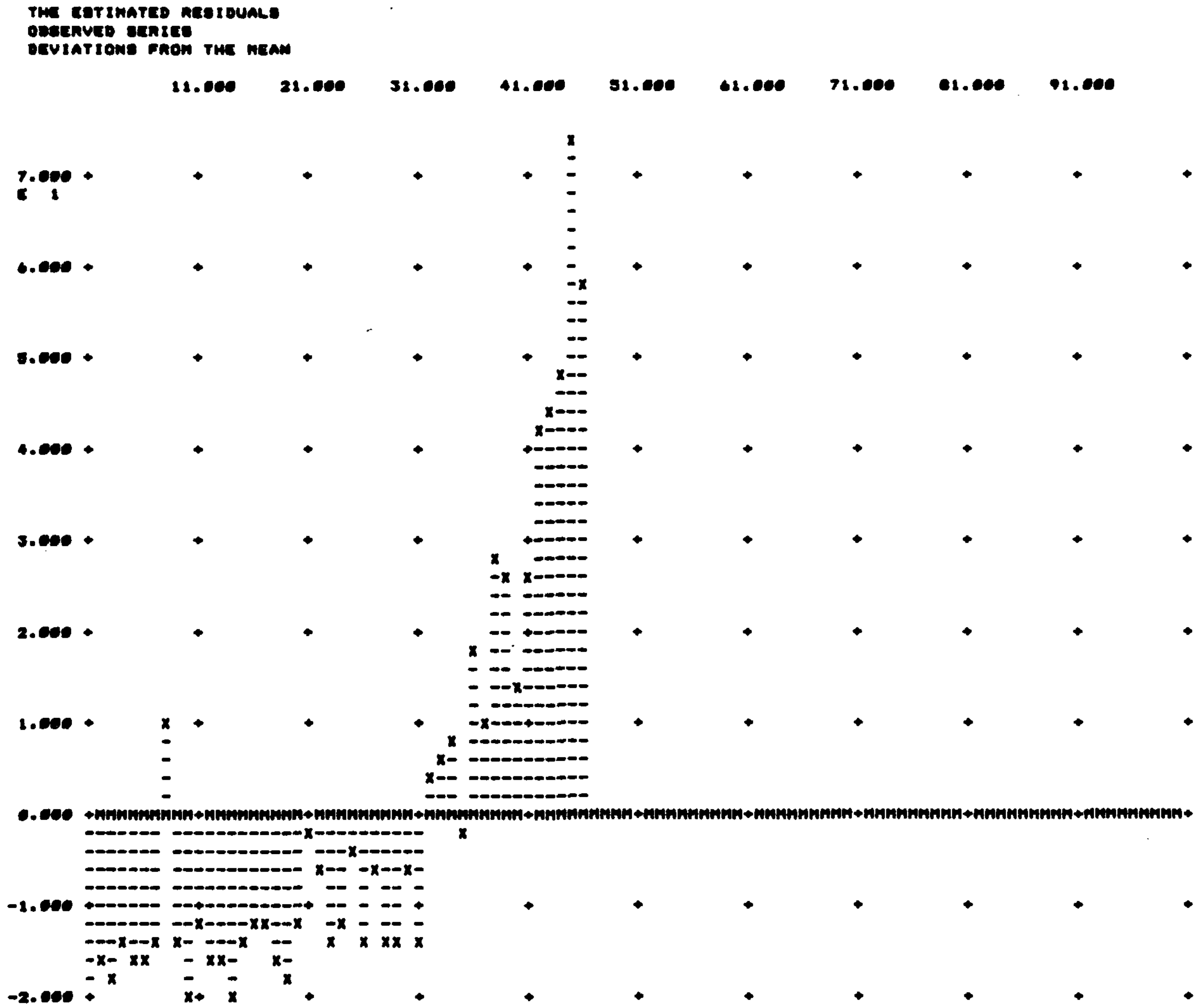
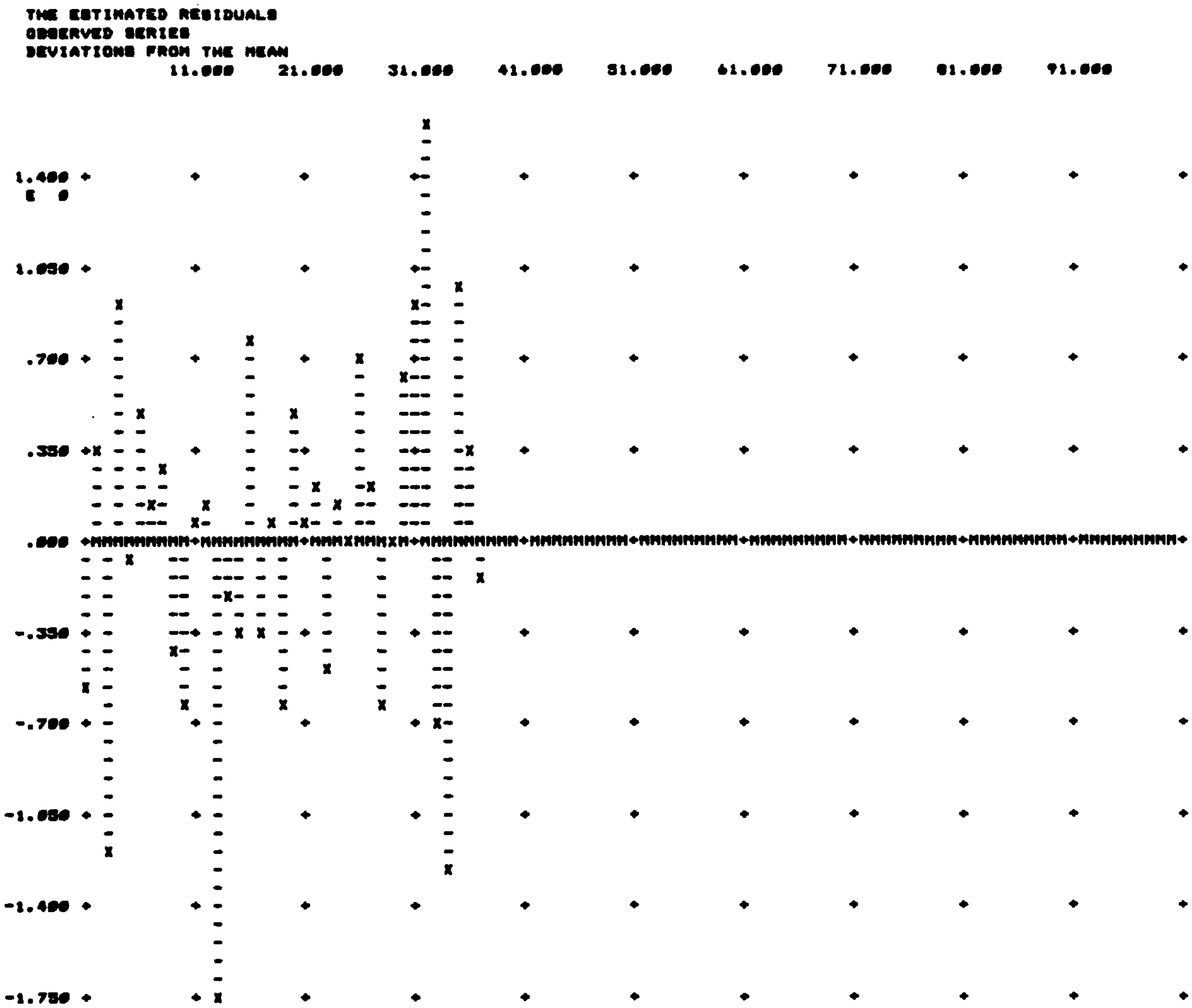


Figure 18

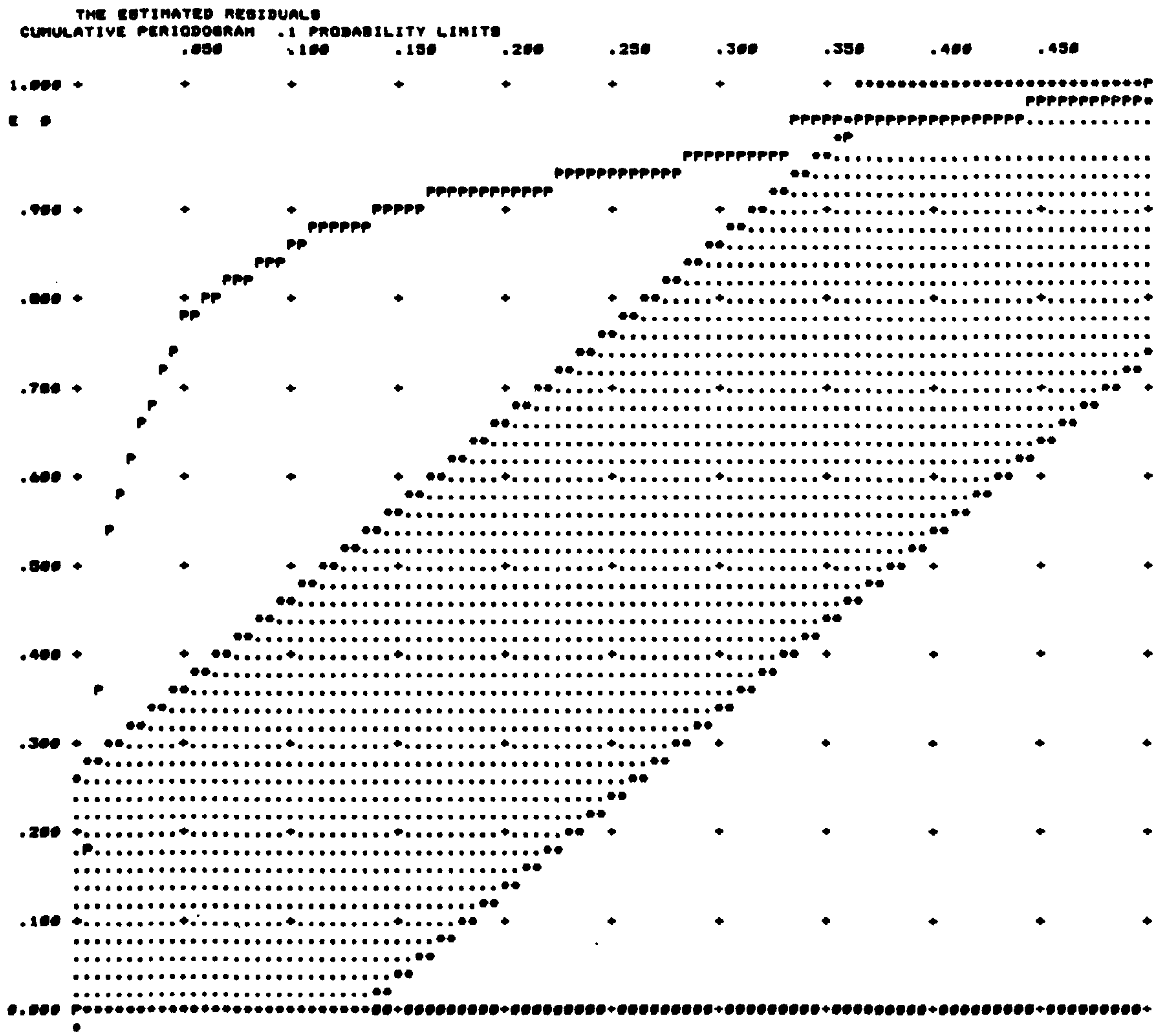
Deviations from the Mean
Time Series Model



The periodogram below should be compared to Figure 14. Note that the residuals do not fit the graph at all in this periodogram, demonstrating that the residuals from the 'Old Method' are still autocorrelated

Figure 19

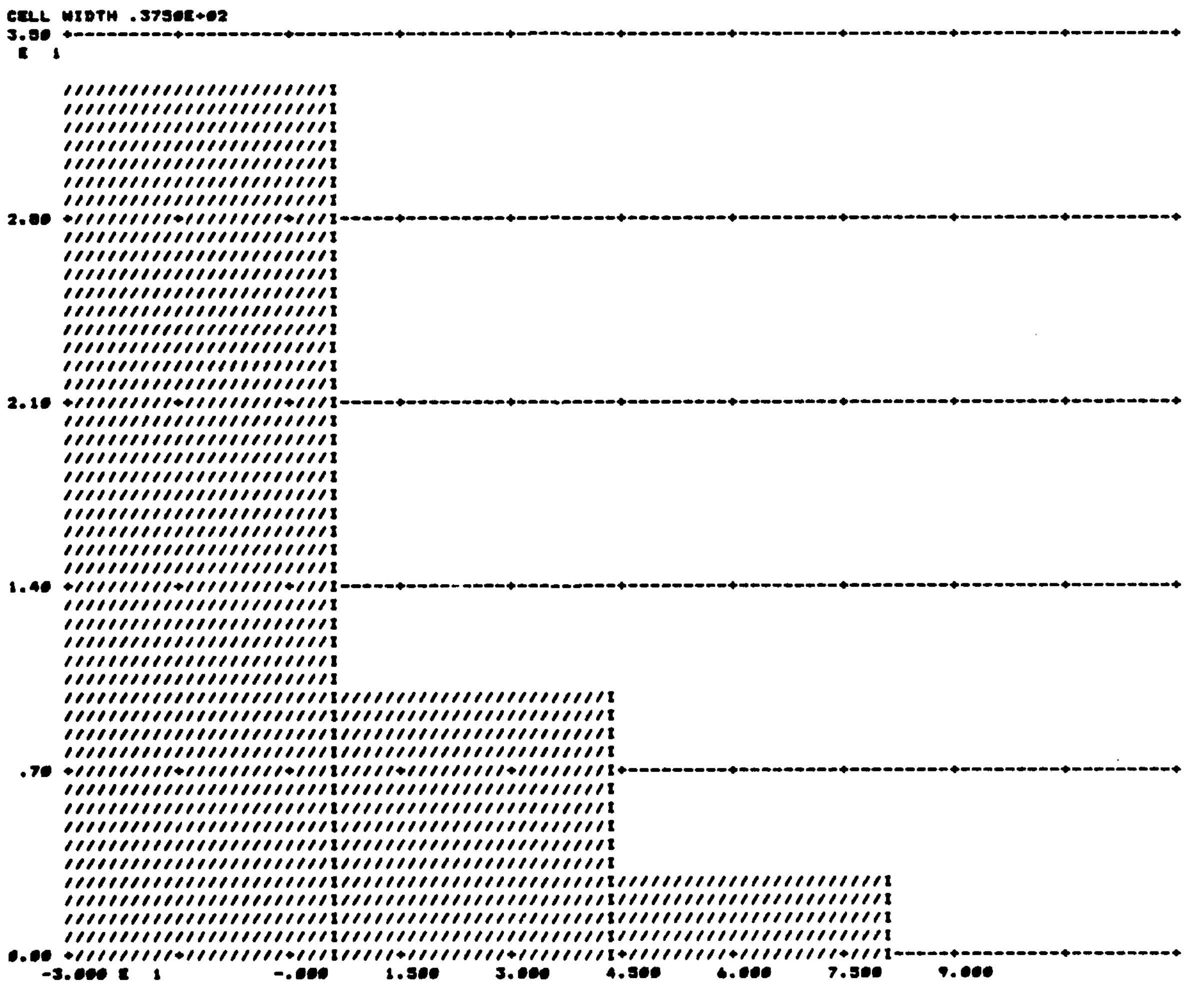
Periodogram for the 'Old Method'



This histogram is compared to Figure 15, this plot is skewed to the right and Figure 15 is near perfect. The histogram is not as good of an indicator of fit as the periodogram and spectrogram and should not be relied on, exclusive of the other indicators.

Figure 20

Histogram
'Old Method'



The linear equation, $Y_t = a_Ø + a_1X_t + e_t$, is put in the form of the transfer function where $Y_t = (\omega_Ø)X_t$. The factor $a_Ø$ takes the expected value zero. The estimated value of input lag 1, parameter order Ø, in Figure 21, .ØØØ14143, represents $\omega_Ø$. Compare also the residual mean square value in both figures. The transfer function model portrayed here is a (Ø,1,Ø). When the time factor of the data is ignored, this is the type of model and fit that will occur.

Figure 21

Summary of Model
'Old Method'

```
*************************************************************************************************

DATA - X = ACTUAL FLYING HOURS (OLD METHOD)                                    47 OBSERVATIONS
       Y = WUC:14FBØ EL COMP ASSY (OLD METHOD)

DIFFERENCING ON Y - NONE

DIFFERENCING ON X - NONE

*************************************************************************************************

NOISE MODEL PARAMETERS

*************************************************************************************************

PARAMETER        PARAMETER        PARAMETER        ESTIMATED              95 PER CENT
 NUMBER            TYPE             ORDER            VALUE        LOWER LIMIT      UPPER LIMIT

*************************************************************************************************

*************************************************************************************************

TRANSFER FUNCTION PARAMETERS

*************************************************************************************************

   1              INPUT LAG 1        Ø             .14143E-Ø4     -.3Ø495E-Ø4      .5878ØE-Ø4

   2              INPUT LAG 1        1            -.1Ø641E-Ø4     -.55244E-Ø4      .33963E-Ø4

*************************************************************************************************

OPTIMUM VALUE OF D IS  Ø

*************************************************************************************************

OTHER INFORMATION AND RESULTS

*************************************************************************************************
RESIDUAL SUM OF SQUARES          .24Ø74E+Ø5     44 D.F.      RESIDUAL MEAN SQUARE        .54714E+Ø3

NUMBER OF RESIDUALS                   46                     RESIDUAL STANDARD ERROR     .23391E+Ø2
```

Figure 22 demonstrates that there is correlation between the series. Compare this figure to Figure 16.

Figure 22

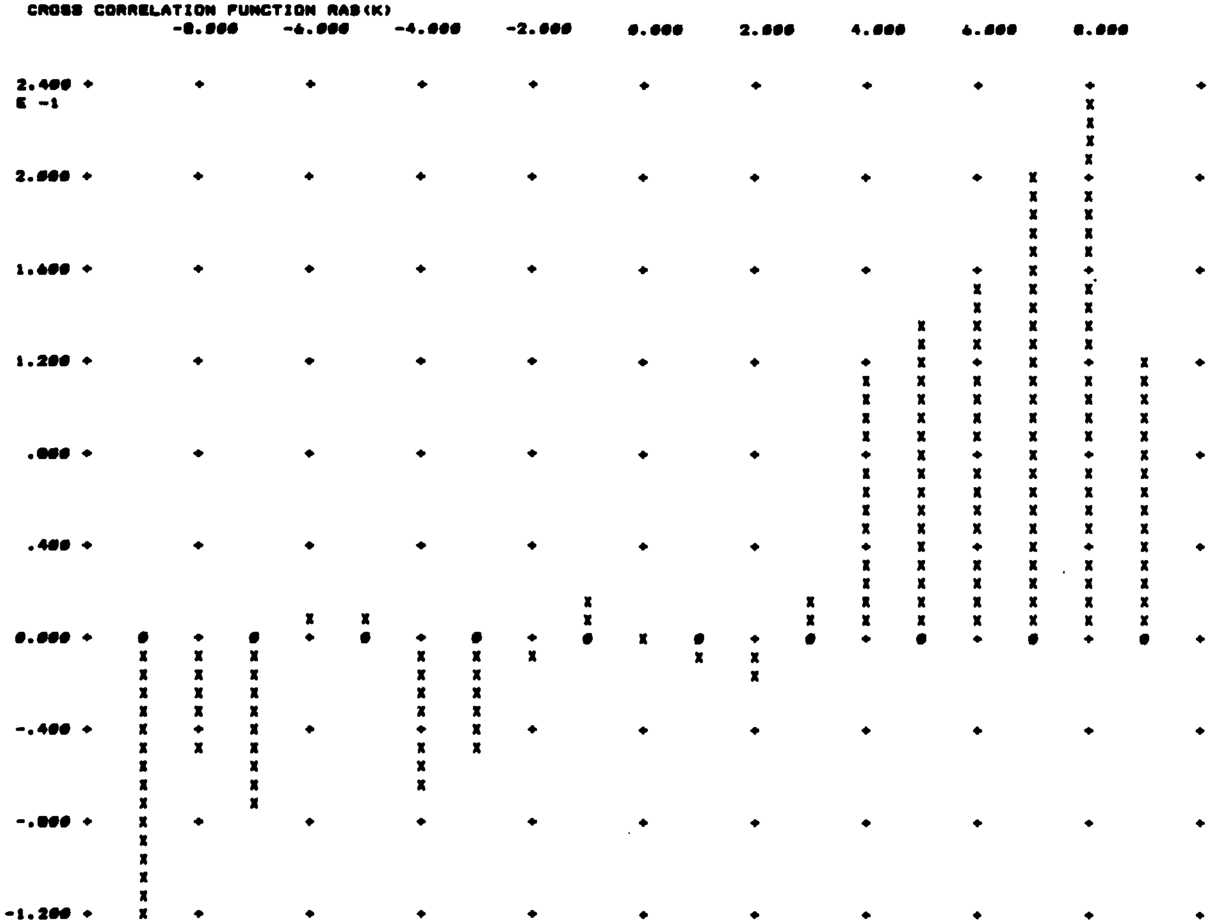
Cross Correlations
'Old Method'

SERIES 1 - PREWHITENED ACTUAL FLYING HOURS (OLD METHOD)
SERIES 2 - THE ESTIMATED RESIDUALS

MEAN OF SERIES 1 = .14027E+04
ST. DEV. OF SERIES 1 = .15510E+06
MEAN OF SERIES 2 = .41023E+00
ST. DEV. OF SERIES 2 = .22073E+02

NUMBER OF LAGS ON SERIES 1	CROSS CORRELATION	NUMBER OF LAGS ON SERIES 2	CROSS CORRELATION
0	-.000	0	-.000
1	-.000	1	.017
2	-.014	2	-.010
3	.014	3	-.050
4	.121	4	-.066
5	.137	5	.000
6	.153	6	.007
7	.194	7	-.072
8	.229	8	-.048
9	.121	9	-.122

A - PREWHITENED ACTUAL FLYING HOURS (OLD METHOD)
B - THE ESTIMATED RESIDUALS
CROSS CORRELATION FUNCTION RAB(K)



CHAPTER 4

CONCLUSIONS AND RECOMMENDATIONS

The last two sections in Chapter 3 demonstrated multivariate time series analysis with the data fitting a model in the first section and the data left 'raw' in the last section. The two sections used the same pair of time series data, but it can easily be seen that when the data is left in it's raw state that it does not fit into a model. This state is similar to that which is presently used to forecast spares requirements. This chapter will draw some conclusions about the study and make some recommendations about how it can be improved and incorporated into the Air Force system of spares forecasting.

Findings

An examination of the transfer function model, in the section titled The Transfer Function Model, of Chapter 3 shows that there is a seven period time lag for the dependent variable, WUC:14FBØ, before the independent variable, actual flying hours, has an effect on it. It was also shown that both variables were non-stationary and had to be made stationary before they could be used. Both series had autoregressive and moving average components and the interrela-

tionships within each series had to be dealt with before the intrarelationships between them could be found.

These facts argue against the linearity assumption discussed in Chapters 1 and 2. Comparing the transfer function model with the 'Old Method' model, described in Chapter 3, demonstrates a clear difference between the two which would produce very different forecasts. The 'Old Method' model does not remove the correlation between and within the series, as demonstrated in Figure 19. This figure demonstrates that the relationship is not a linear one, and should not be used without first considering the elements which produced the much better fit shown in Figure 14. Without first removing the "within and between structure" relationships, it is not possible to accurately forecast with the raw data.

Problems with Using Time Series Analysis

Time series analysis should use at least 50 and preferably 100 observations to realize the full benefit of its powerful ability to produce accurate forecasts. This thesis used selected WUC's from the F-16 which did not have that many observations because of it's recent introduction into the Air Force inventory. As this aircraft become older the methods demonstrated in this thesis will become easier to use. That is, with more observations to work with, the patterns produced with the TIMES program are more readily identifiable. This would make the modeling process less time consuming and enable more precise identification of the re-

lationships, thereby reducing the iterations required to arrive at the correct model. A rule of thumb in any statistical effort says that "the more observations available, the more accurate the findings will be," this applies equally well to time series analysis.

Conclusions

This thesis has attempted to demonstrate that using the "linearity assumption" in the business of forecasting can lead to errors, because this assumption ignores the time factor inherent in the data collection process. Ignorance of this factor produces forecasting models such as demonstrated in the 'Old Method' section of Chapter 3. This model clearly has cross correlation present between the variables which will cause errors in a forecast. The thrust of the thesis effort has been to show that time series analysis will produce models better suited to forecasting future spares requirements. When the models produced with time series methods are compared to a model of the same data, produced without the benefit of time series methods, then time series forecasting becomes a more intuitively appealing method of estimating what the future spares requirements might be.

With all the time series analysis programs readily available, and the increasing availability of computer resources to the IM's, the assumption that demands per flying hour is just a linear ratio need no longer be made. In addition, the improved data collection systems being introduced

enable the IM to get all the data needed to make more accurate forecasts for the spares requirements. This could lend itself to dollar savings as well as improved readiness and support of weapon systems.

The TIMES software package belongs to the Air Force and can be booted to any main frame computer that is capable of compiling FORTRAN ver. 5 (20). There is also a software program called SIBYL/RUNNER (13) which is available on the Harris 500. This is a more user friendly time series package although I do not believe it is as powerful as the TIMES program. The SPSS and BMDP packages also include time series analysis programs.

Once a model is developed, the program allows it to be continually updated with future observations. This implies that once the effort to develop models for each WUC or LRU is accomplished, it is a simple matter of adding the latest observations to update the forecast. All of the software packages allow the user to specify forecasts for future periods which they define. Updating the model periodically will assure that long term forecasts remain accurate.

Recommendations

The models in this thesis should be verified with additional observations as they become available. Also, the computer resources available to the Item Manager should have the TIMES software package implemented so that they can begin using it to aid them in their support of the various

weapon systems. The initial effort to develop forecasting models will pay for itself in future time saved, improved support and readiness of the individual systems. The allocation of funds for spares is never enough, especially if the spares purchased are based on an assumption that their utilization is based on a straight linear relationship with actual flying hours. There is a lot of concern that support based on this assumption in peacetime will be short of some requirements in a wartime situation. This concern is greatest where the more expensive LRU's are the required spare (7;8;9;10;11;12). The required spare should be available when needed, regardless of its cost, and using time series methods to forecast should increase the probability that it will be there, without increasing the entire inventory.

APPENDICES

APPENDIX A

THE DATA

Figure A1

The Data Used In Time Series Models

Date	Actual Flying Hours	Removals for Work Unit Codes				
		42GB0	14FB0	24EBA	46AF0	46AN0
7906	411.55	0	2	2	0	0
7907	552.35	0	2	0	0	0
7908	516.50	0	5	0	0	0
7909	945.10	0	3	0	0	0
7910	1226.35	0	7	0	1	0
7911	1410.80	1	5	0	0	0
7912	1286.15	1	5	0	0	0
8001	1554.50	3	8	0	3	0
8002	1902.45	0	31	0	2	0
8003	2173.05	0	9	0	0	0
8004	2635.55	1	2	1	1	0
8005	2880.15	8	9	0	0	0
9006	3019.75	1	5	1	1	0
8007	3423.05	4	12	0	1	0
8008	3523.00	0	6	0	4	0
8009	3195.60	2	7	0	2	0
8010	4606.95	2	10	1	2	2
8011	4150.80	2	9	2	0	2
8012	3922.30	1	5	0	2	1
8101	4288.90	1	4	2	0	1
8102	4861.25	4	10	0	0	3
8103	6093.80	0	19	0	0	0
8104	6394.95	3	15	1	2	1
8105	6384.50	3	14	0	4	2
8106	7131.70	1	16	1	4	0
8107	8212.45	3	18	3	1	0
8108	1926.08	12	7	0	2	1
8109	6686.05	7	16	4	1	0
8110	8748.00	6	14	0	2	2
8111	8291.15	5	12	1	2	2
8112	8884.20	1	16	6	1	1
8201	9562.85	7	7	3	3	5
8202	10150.75	13	26	0	1	1
8203	10752.20	15	34	3	4	4
8204	10941.95	4	35	4	1	1
8205	11475.25	9	19	4	0	1
8206	12829.65	11	39	4	3	1
8207	12324.05	4	32	3	2	1
8208	13628.70	8	57	2	4	1
8209	12026.50	9	54	0	1	1
8210	13626.40	9	36	1	9	5
8211	14187.30	5	47	4	3	1
8212	13188.40	11	64	5	4	3
8301	13801.60	13	66	5	7	2
8302	14361.10	18	71	2	2	14
8303	16156.15	7	97	7	4	7
8304	15155.40	10	79	8	4	6

APPENDIX B

THE UNIVARIATE MODELS

Figure B1

Final Periodogram - WUC:42GBØ

The Estimated Residuals - WUC:42GBØ Charger AC Battery
Cumulative Periodogram .1 Probability Limits

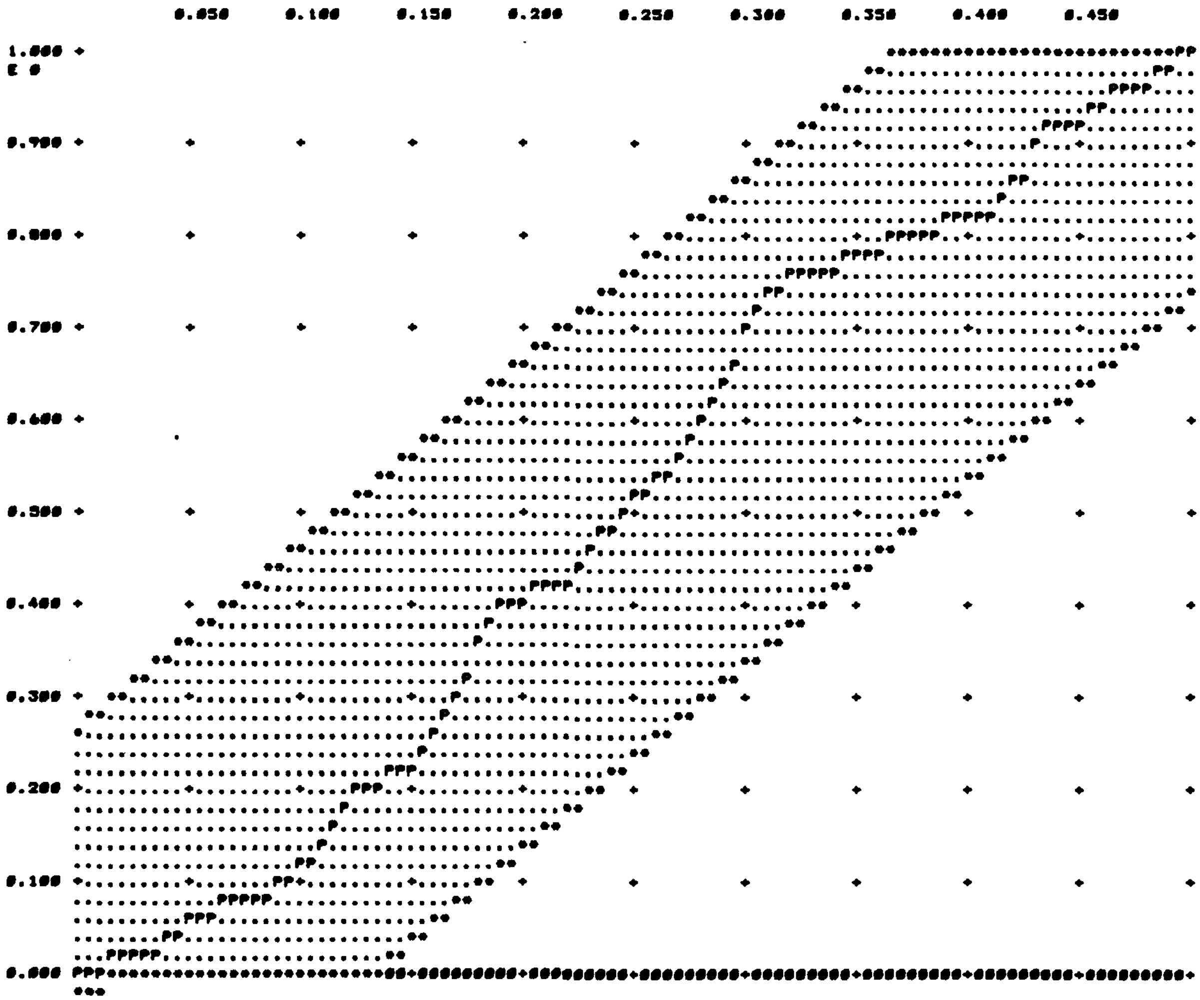


Figure B2

Summary of Model - WUC:42GBØ

DATA - Z = WUC:42GB0 CHARGER AC BATTERY 47 OBSERVATIONS

DIFFERENCING ON Z - 1 OF ORDER 1

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	MOVING AVERAGE 1	1	0.74736E+00	0.53800E+00	0.95671E+00

OTHER INFORMATION AND RESULTS

RESIDUAL SUM OF SQUARES	0.56117E+03	45 D.F.	RESIDUAL MEAN SQUARE	0.12470E+02
NUMBER OF RESIDUALS	46		RESIDUAL STANDARD ERROR	0.35313E+01

PREWHITENED WUC:42GB0 CHARGER AC BATTERY
LOG10 SPECTRUM SMOOTHING BANDWIDTH = .098 APPROX 95 P.C. CONFIDENCE LIMITS

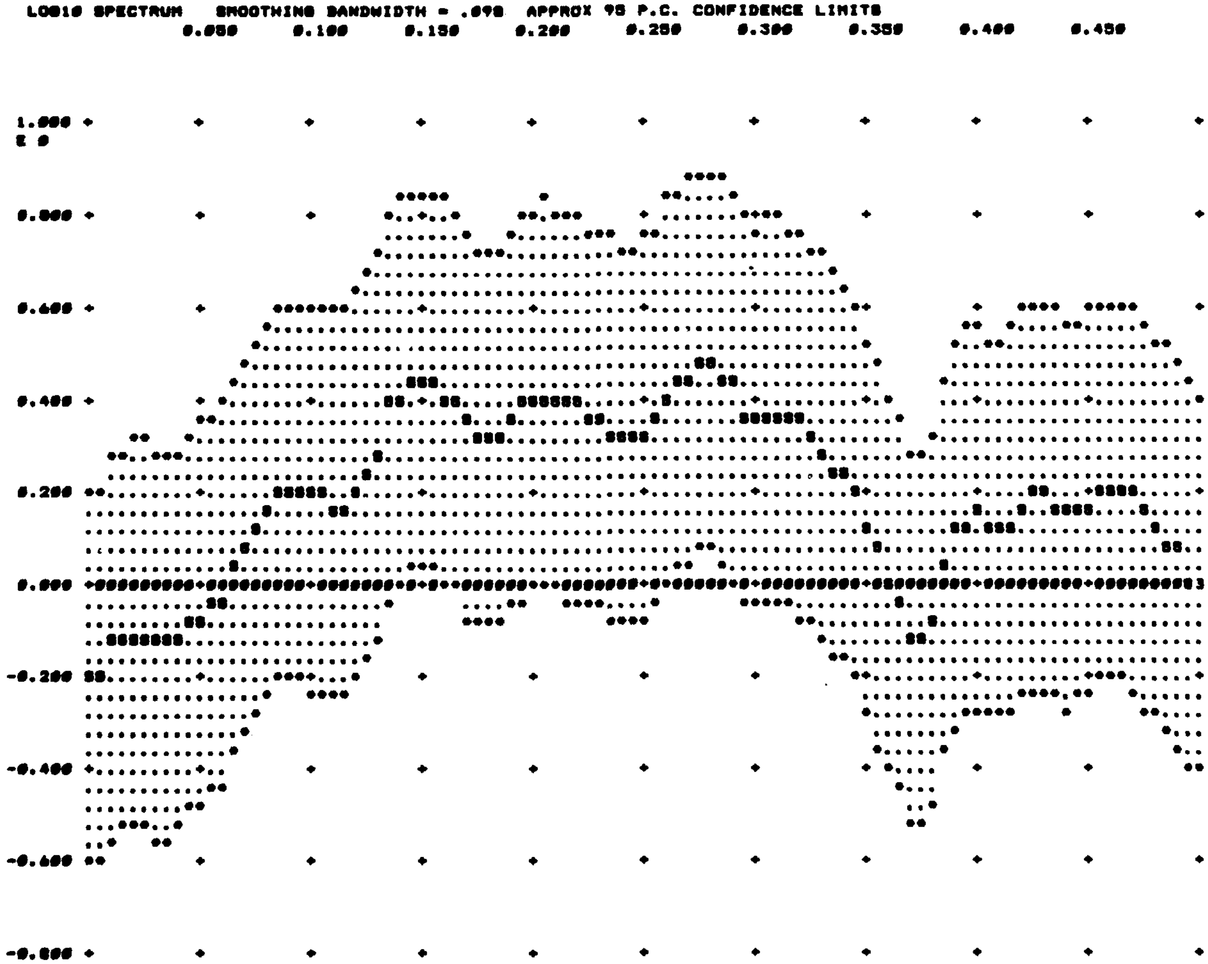


Figure B3

Final Periodogram - WUC:14FBØ

The Estimated Residuals - WUC:14FBØ El Comp Assy
Cumulative Periodogram .1 Probability Limits

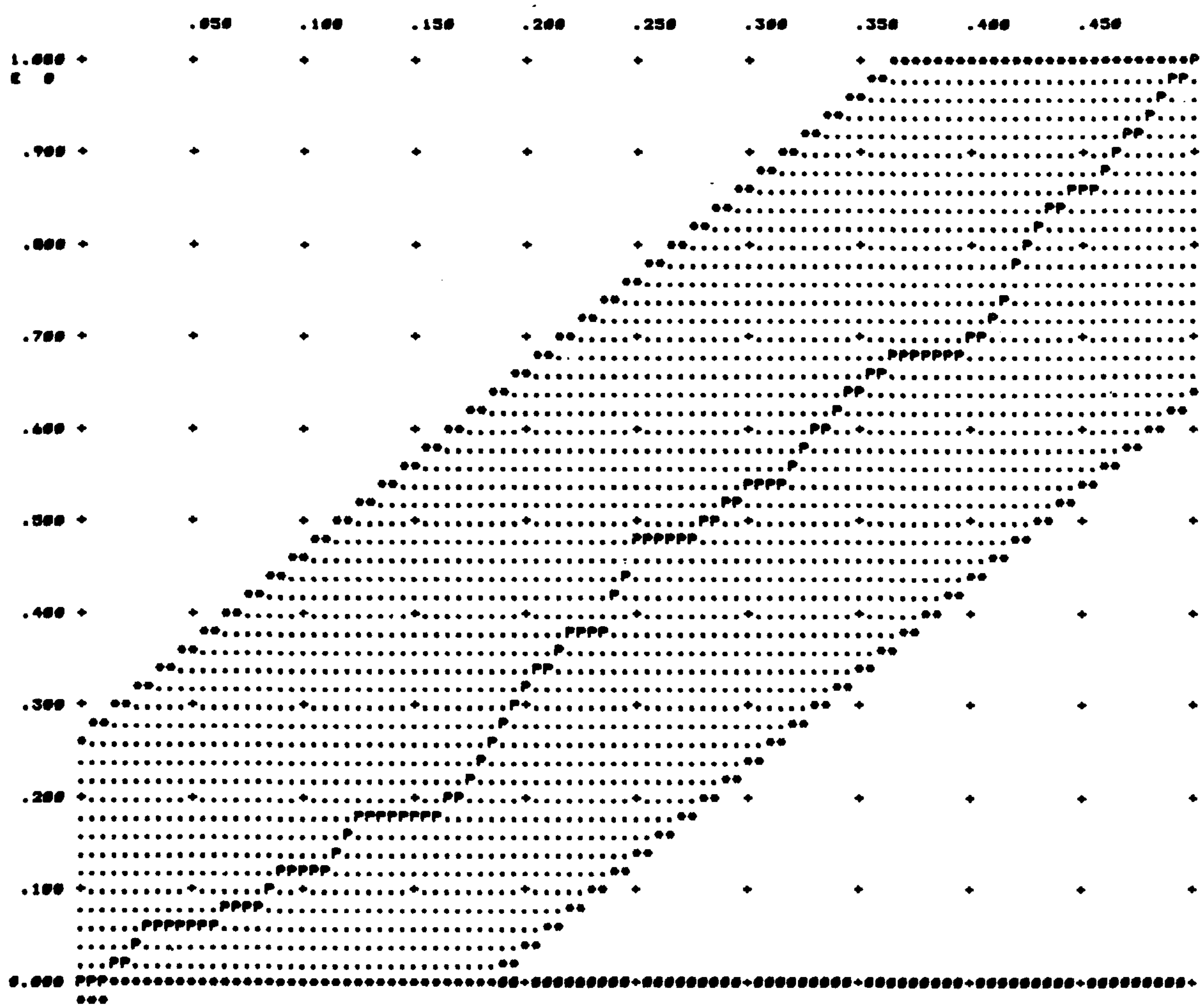


Figure B4

Summary of Model - WUC:14FBØ El Comp Assy

DATA - Z = WUC:14FBØ EL COMP ASSY — 47 OBSERVATIONS

DIFFERENCING ON Z - 1 OF ORDER 1

MODEL DEVELOPED WITH TRANSFORMATION DATA = LOG(Z(T)+Ø.)

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	AUTOREGRESSIVE 1	1	-.6Ø762E-Ø1	-.39195E+ØØ	.25443E+ØØ
2	AUTOREGRESSIVE 1	2	-.47673E+ØØ	-.77945E+ØØ	-.174Ø2E+ØØ
3	MOVING AVERAGE 1	1	.75544E+ØØ	.4694ØE+ØØ	.1Ø414E+Ø1

OTHER INFORMATION AND RESULTS

RESIDUAL SUM OF SQUARES	.336Ø9E+Ø2 41 D.F.	RESIDUAL MEAN SQUARE	.8216ØE+ØØ
NUMBER OF RESIDUALS	44	RESIDUAL STANDARD ERROR	.9Ø646E+ØØ

PREWHITENED WUC:14FBØ ELC COMP ASSY
LOG1Ø SPECTRUM SMOOTHING BANDWIDTH = .Ø98 APPROX 95 P.C. CONFIDENCE LIMITS

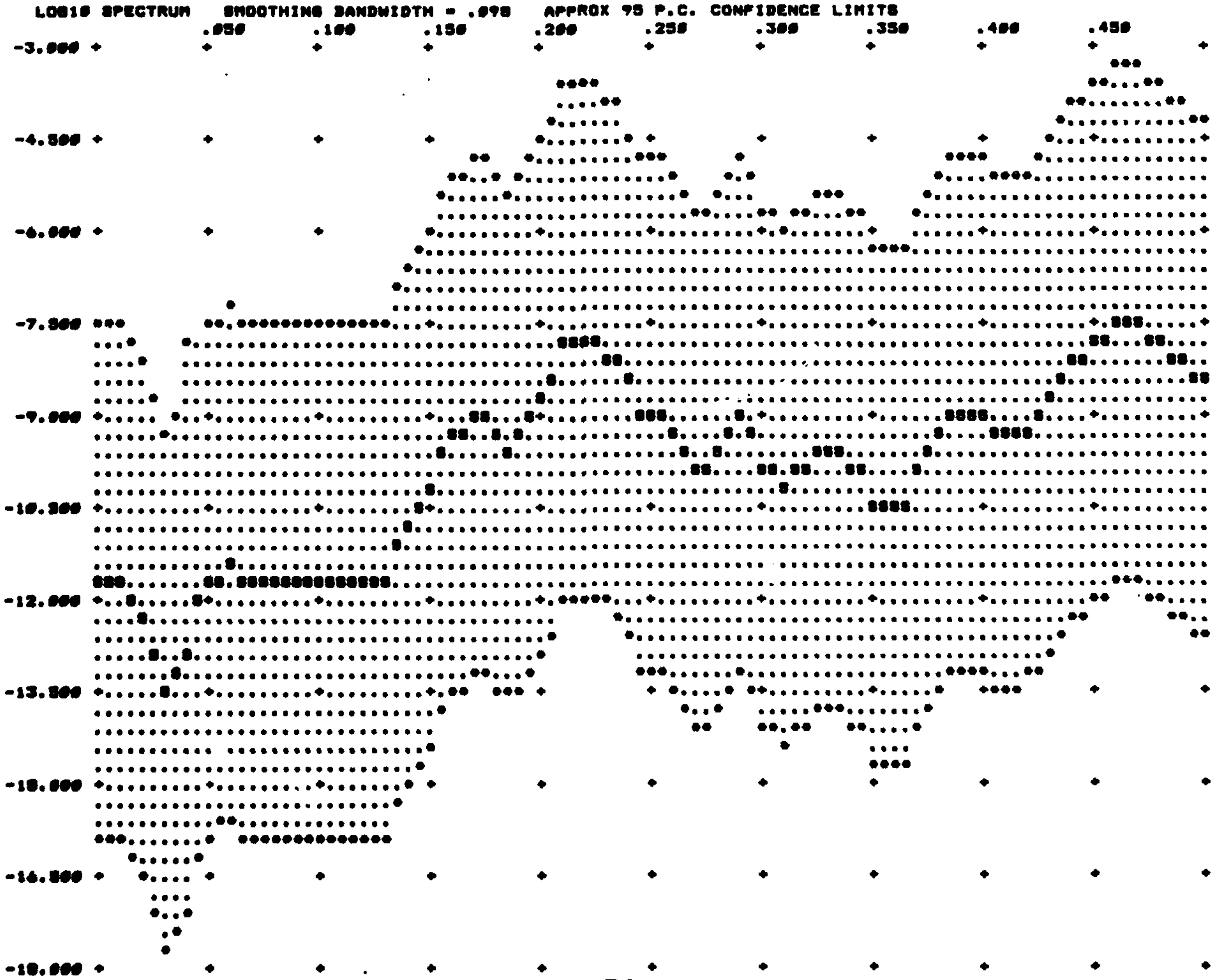


Figure B5

Final Periodogram - WUC:24EBA

The Estimated Residuals - WUC:24EBA PTO Shaft
Cumulative Periodogram .1 Probability Limits

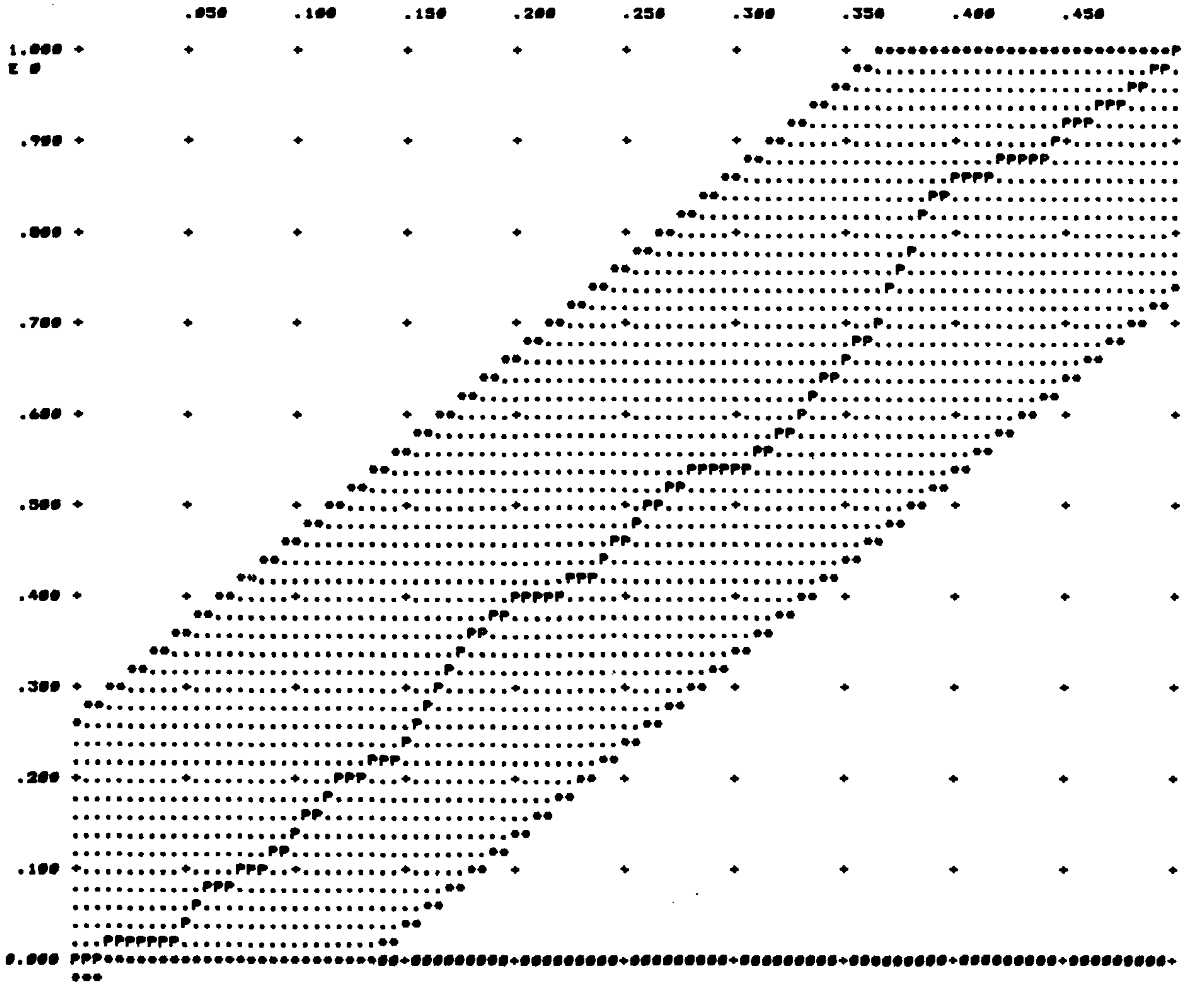


Figure B6

Summary of Model - WUC:24EBA PTO Shaft

DATA - Z = WUC:24EBA PTO SHAFT — 47 OBSERVATIONS

DIFFERENCING ON Z - 1 OF ORDER 1

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	AUTOREGRESSIVE 1	1	-.12117E+00	-.67804E+00	.43570E+00
2	AUTOREGRESSIVE 1	2	-.31575E+00	-.71396E+00	.82458E-01
3	MOVING AVERAGE 1	1	.52364E+00	-.32225E-01	.10795E+01

OTHER INFORMATION AND RESULTS

RESIDUAL SUM OF SQUARES .11858E+03 41 D.F. — RESIDUAL MEAN SQUARE .28702E+01

NUMBER OF RESIDUALS 44 — RESIDUAL STANDARD ERROR .17001E+01

PREWHITENED WUC:24EBA PTO SHAFT

LOG10 SPECTRUM SMOOTHING BANDWIDTH = .090 APPROX 95 P.C. CONFIDENCE LIMITS

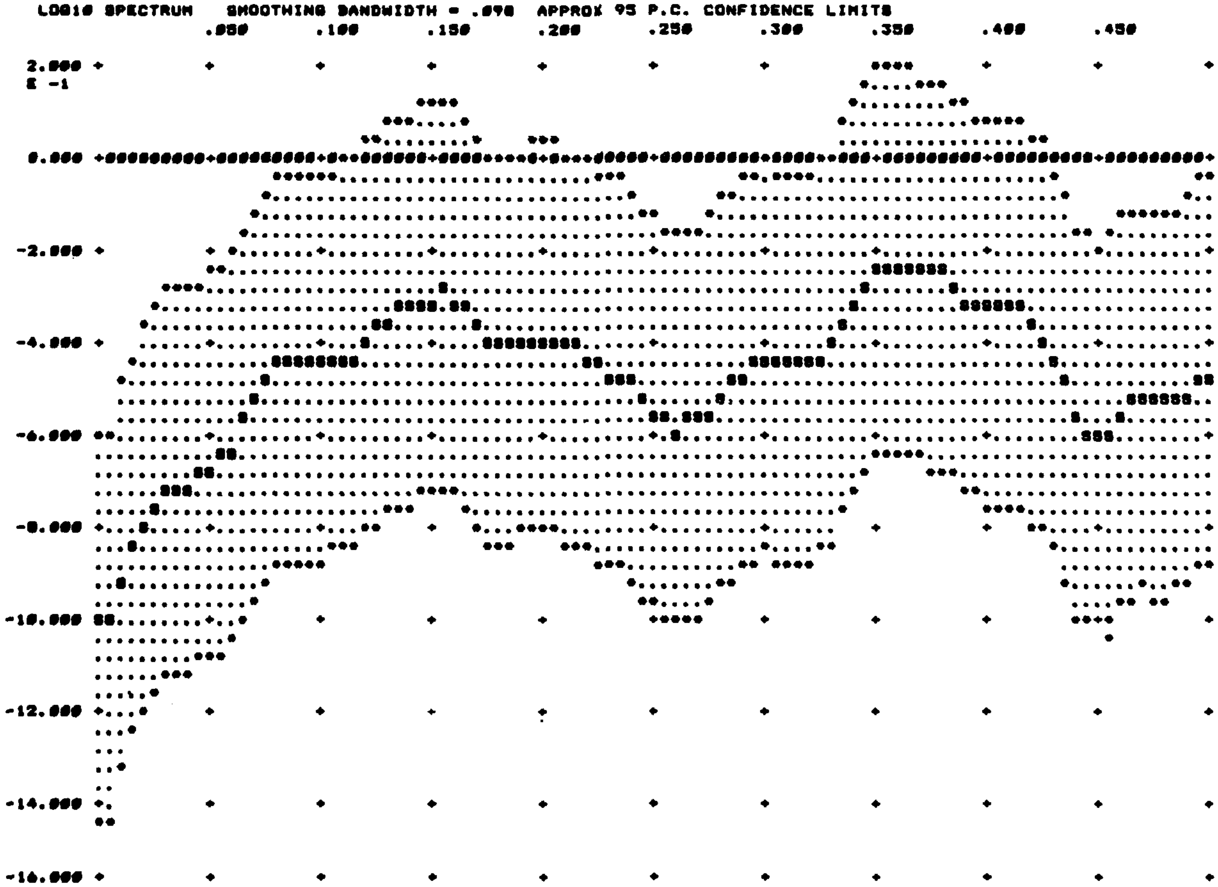


Figure B7

Final Periodogram - WUC:46AFØ

The Estimated Residuals - WUC:46AFØ Proport Fuel Flow
Cumulative Periodogram .1 Probability Limits

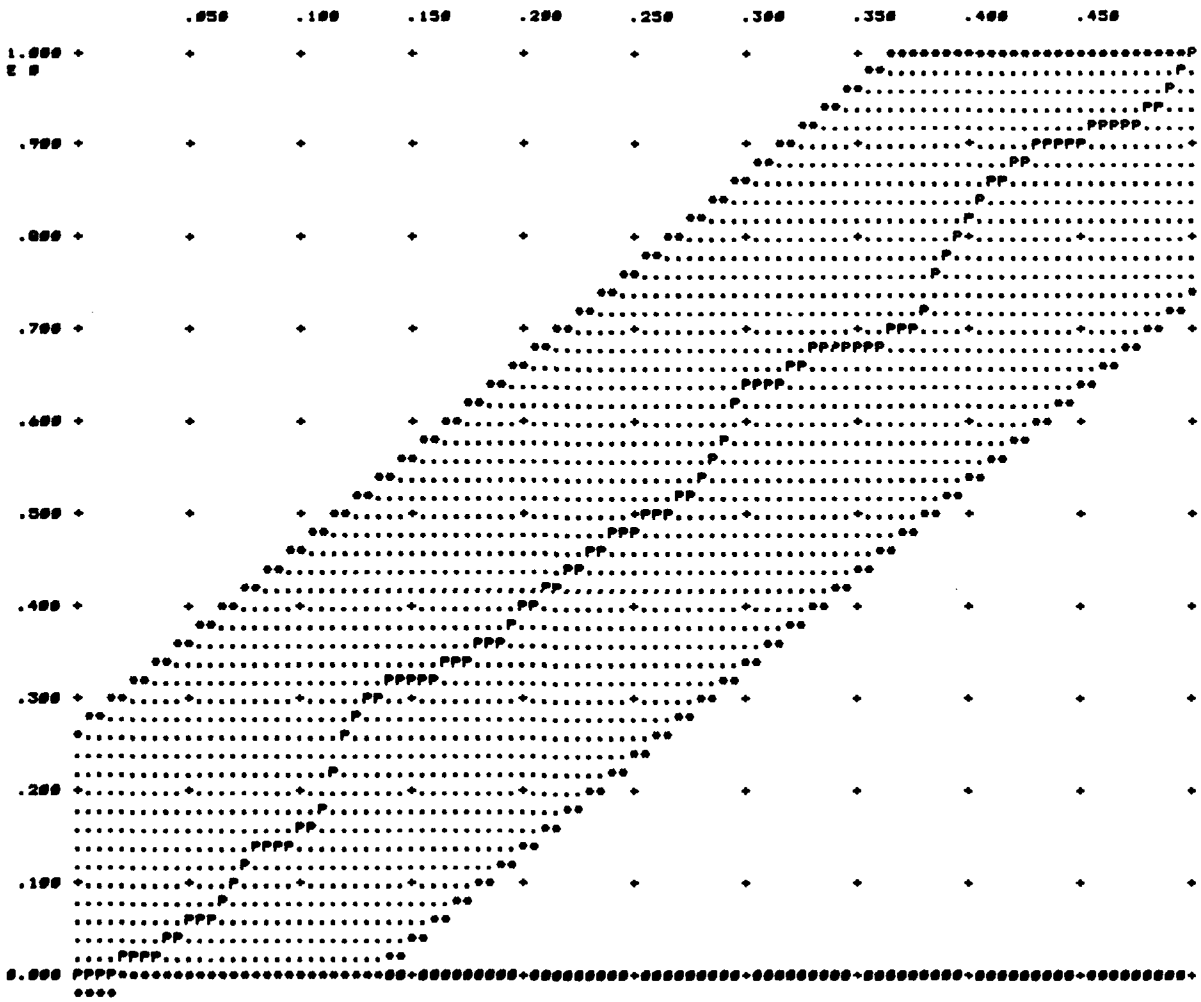


Figure B8

Summary of Model - WUC:46AFØ Proport Fuel Flow

DATA - Z = WUC:46AFØ PROPORT FUEL FLOW — 47 OBSERVATIONS

DIFFERENCING ON Z - 1 OF ORDER 1

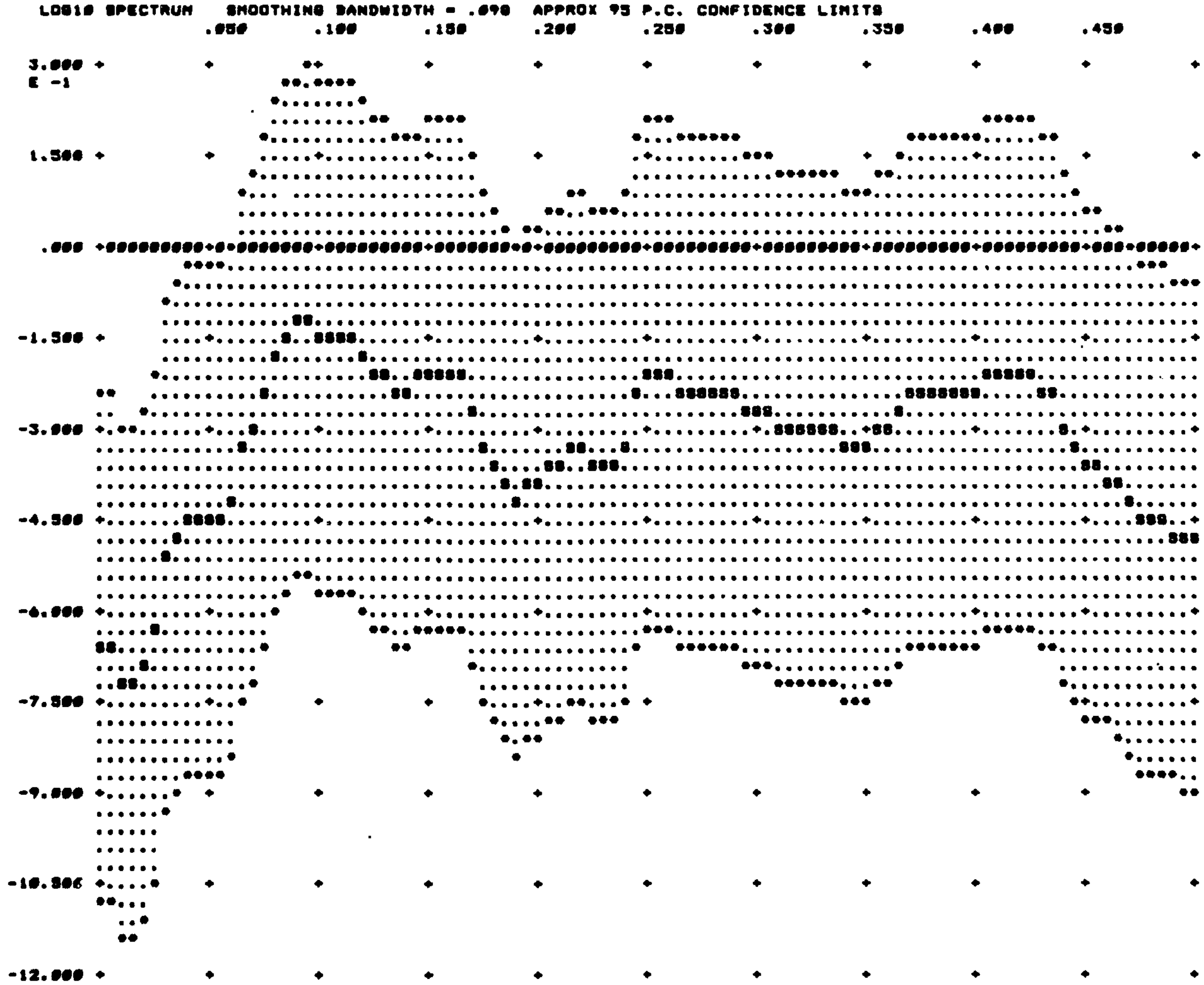
PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	AUTOREGRESSIVE 1	1	-.10442E+00	-.45220E+00	.24337E+00
2	AUTOREGRESSIVE 1	2	-.38446E+00	-.73785E+00	-.31070E-01
3	MOVING AVERAGE 1	1	.76077E+00	.50272E+00	.10348E+01

OTHER INFORMATION AND RESULTS

RESIDUAL SUM OF SQUARES .15320E+03 41 D.F. RESIDUAL MEAN SQUARE .37366E+01

NUMBER OF RESIDUALS 44 RESIDUAL STANDARD ERROR .19330E+01

PREWHITENED WUC:46AFØ PROPORT FUEL FLOW
LOG10 SPECTRUM SMOOTHING BANDWIDTH = .090 APPROX 95 P.C. CONFIDENCE LIMITS



AD-A135 531 THE USE OF TIME SERIES ANALYSIS TO DEVELOP SPARES REQUIREMENTS FORECASTS(U) AIR FORCE INST OF TECH WRIGHT-PATTERSON AFB OH SCHOOL OF SYST.. L D TAYLOR

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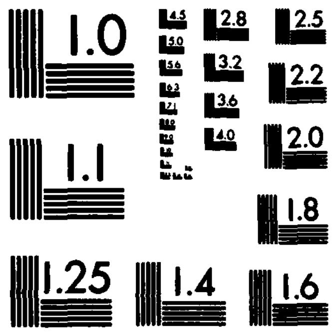


MICROCOPY RESOLUTION TEST CHART
NATIONAL BUREAU OF STANDARDS-1963-A

Figure B9

Final Periodogram - WUC:46ANØ

The Estimated Residuals - WUC:46ANØ Vlv Shutoff Mot Opr
Cumulative Periodogram .1 Probability Limits

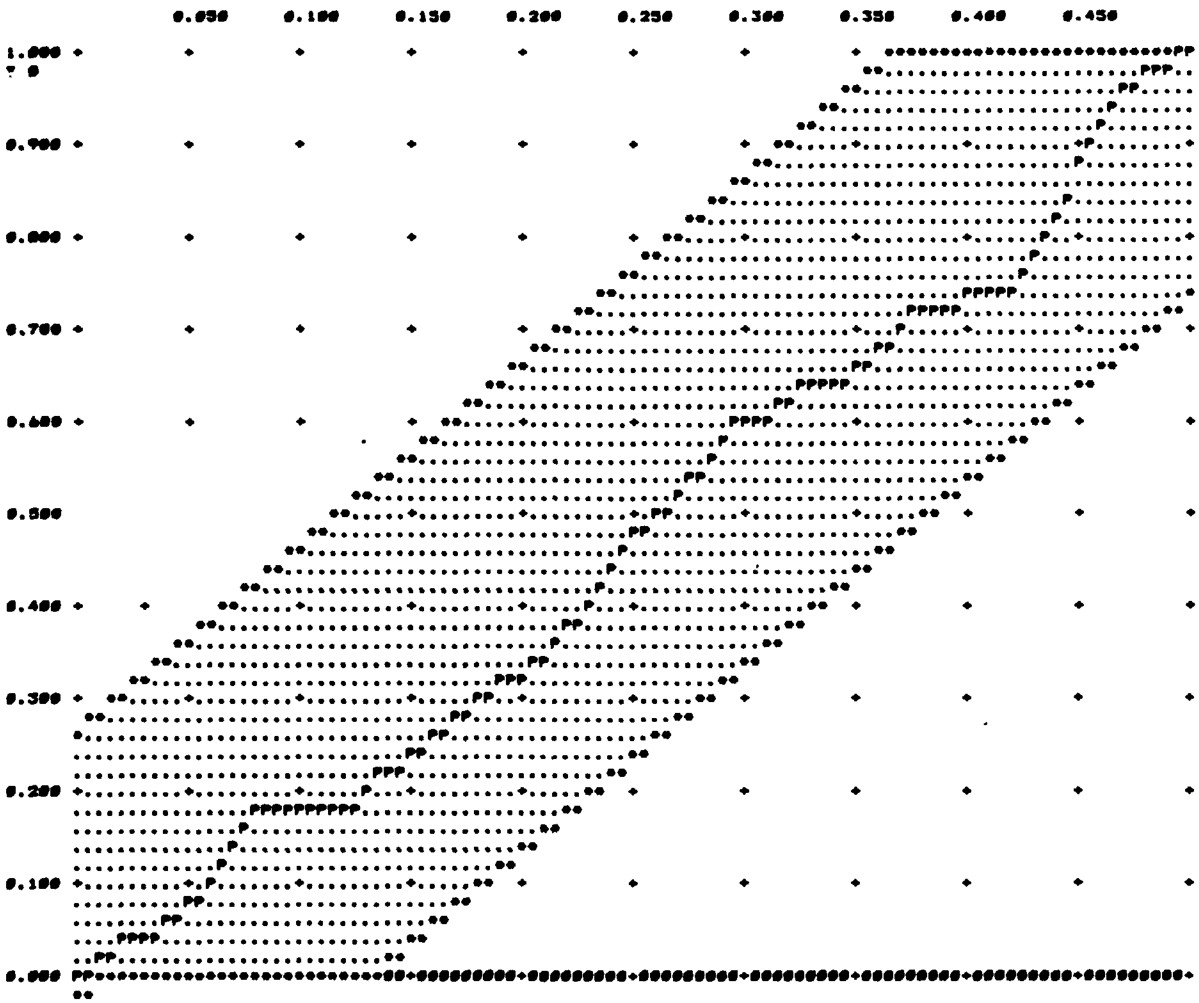


Figure B1Ø

Summary of Model - WUC:14ANØ Vlv Shutoff Mot Opr

DATA - Z = WUC:14ANØ VLV SHUTOFF MOT OPR 47 OBSERVATIONS

DIFFERENCING ON Z - 1 OF ORDER 1

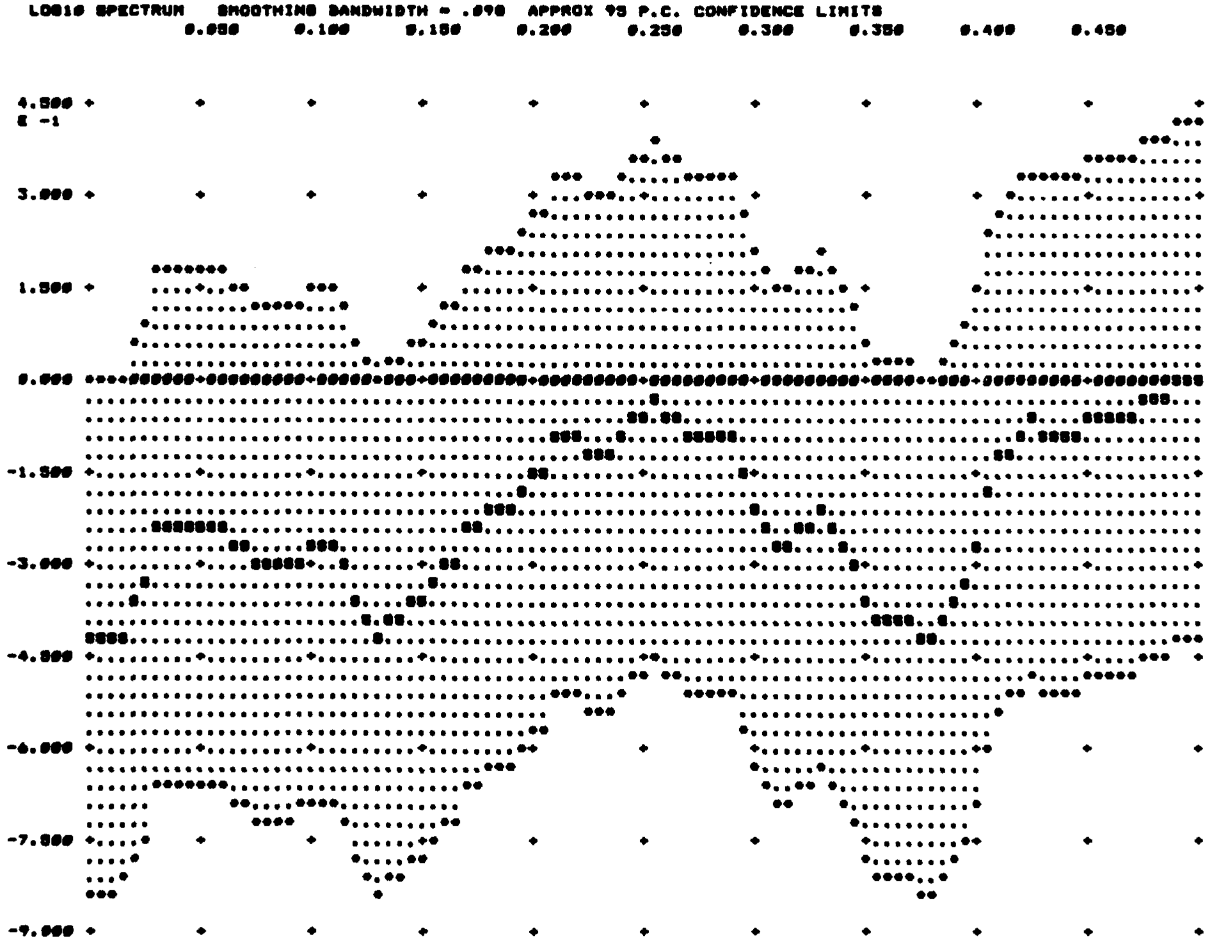
PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	AUTOREGRESSIVE 1	1	-.7Ø241E+ØØ	-.1Ø228E+Ø1	-.38236E+ØØ
2	AUTOREGRESSIVE 1	2	-.281ØØE+ØØ	-.6297ØE+ØØ	Ø.677Ø6E-Ø1

OTHER INFORMATION AND RESULTS

RESIDUAL SUM OF SQUARES Ø.2Ø734E+Ø3 42 D.F. RESIDUAL MEAN SQUARE Ø.49366E+Ø1

NUMBER OF RESIDUALS 44 RESIDUAL STANDARD ERROR Ø.2221ØE+Ø1

PREWHITENED WUC:14ANØ VLV SHUTOFF MOT OPR
LOG1Ø SPECTRUM SMOOTHING BANDWIDTH = .Ø9Ø APPROX 95 P.C. CONFIDENCE LIMITS



APPENDIX C

THE MULTIVARIATE MODELS

. Figure C1

Estimated Impulse Response - WUC42GBØ

X - Prewhitened Actual Flying Hours
Y - Prewhitened WUC:42GBØ Charger AC Battery

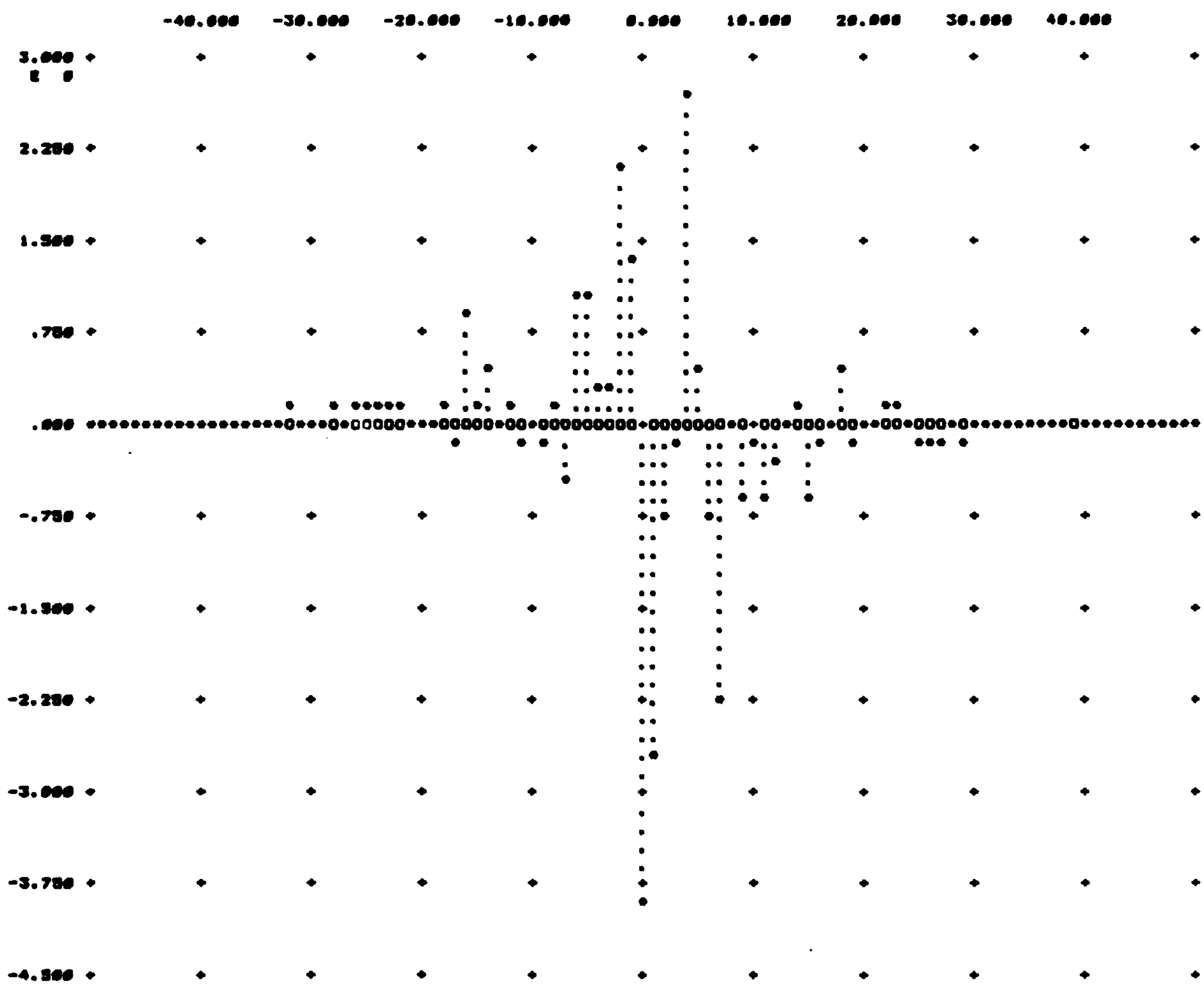


Figure C2

Summary of Model - WUC:42GBØ Charger AC Battery

****

DATA - X = ACTUAL FLYING HOURS — 44 OBSERVATIONS
Y = WUC: 42GBØ CHARGER A-C BATTERY

DIFFERENCING ON Y - NONE

DIFFERENCING ON X - NONE

****

NOISE MODEL PARAMETERS

****

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT

****

****

TRANSFER FUNCTION PARAMETERS

****

1	INPUT LAG 1	Ø	-.48Ø69E+Ø1	-.85659E+Ø1	-.1Ø479E+Ø1
2	INPUT LAG 1	1	.35346E+Ø1	-.2Ø816E+ØØ	.72773E+Ø1
3	INPUT LAG 1	4	-.49247E+Ø1	-.85948E+Ø1	-.12546E+Ø1
4	INPUT LAG 1	7	.52819E+Ø1	.169Ø4E+Ø1	.88734E+Ø1
5	INPUT LAG 1	8	-.19522E+Ø1	-.54665E+Ø1	.15622E+Ø1

****

OPTIMUM VALUE OF B IS Ø

****

OTHER INFORMATION AND RESULTS

****

RESIDUAL SUM OF SQUARES .261Ø8E+Ø3 31 D.F. — RESIDUAL MEAN SQUARE .8422ØE+Ø1

NUMBER OF RESIDUALS 36 — RESIDUAL STANDARD ERROR .29Ø21E+Ø1

Figure C3

Periodogram - WUC:42GB0 Charger AC Battery

The Estimated Residuals
Cumulative Periodogram .1 Probability Limits

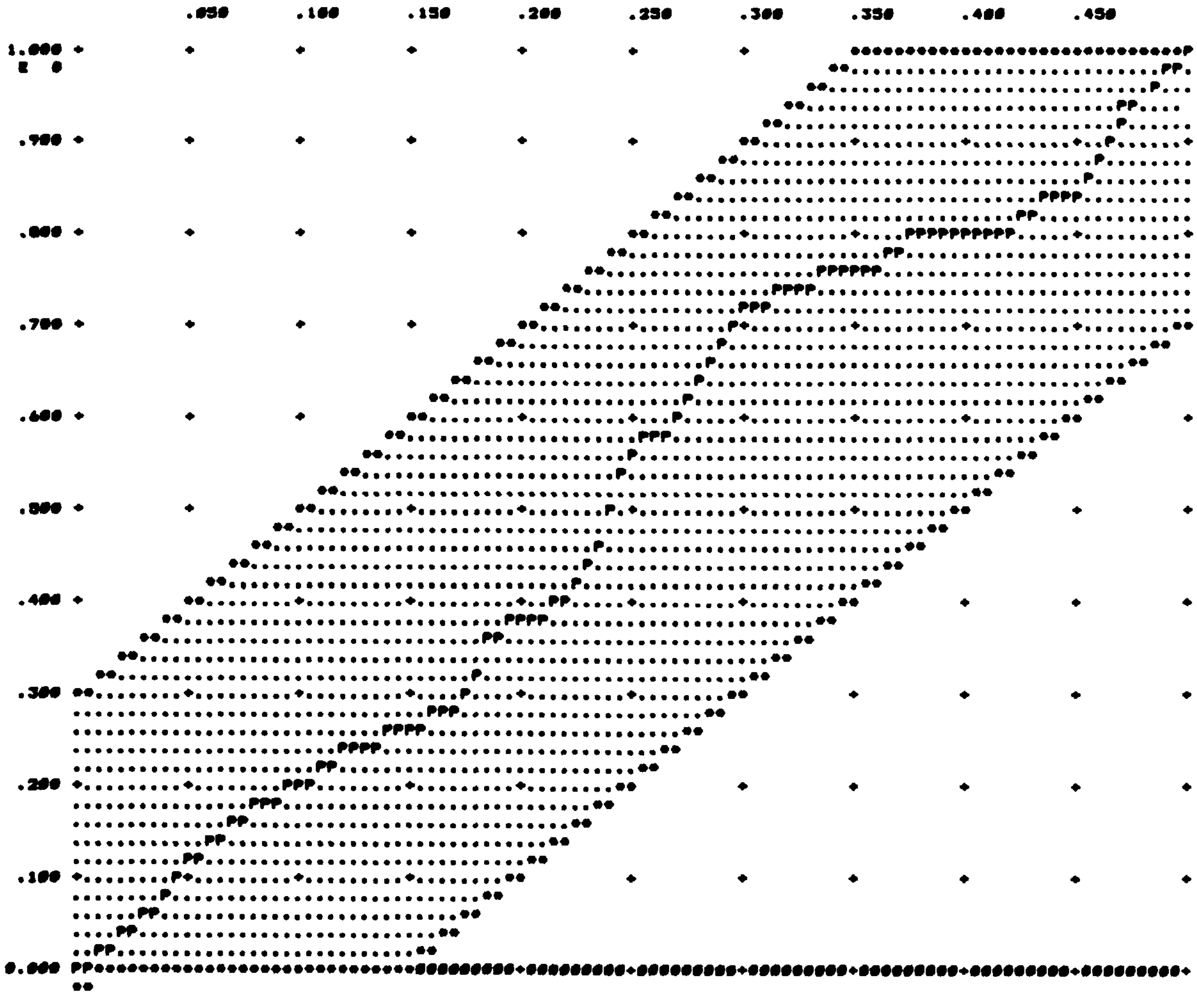


Figure C4

Histogram - WUC:42GB0 Charger AC Battery
The Estimated Residuals

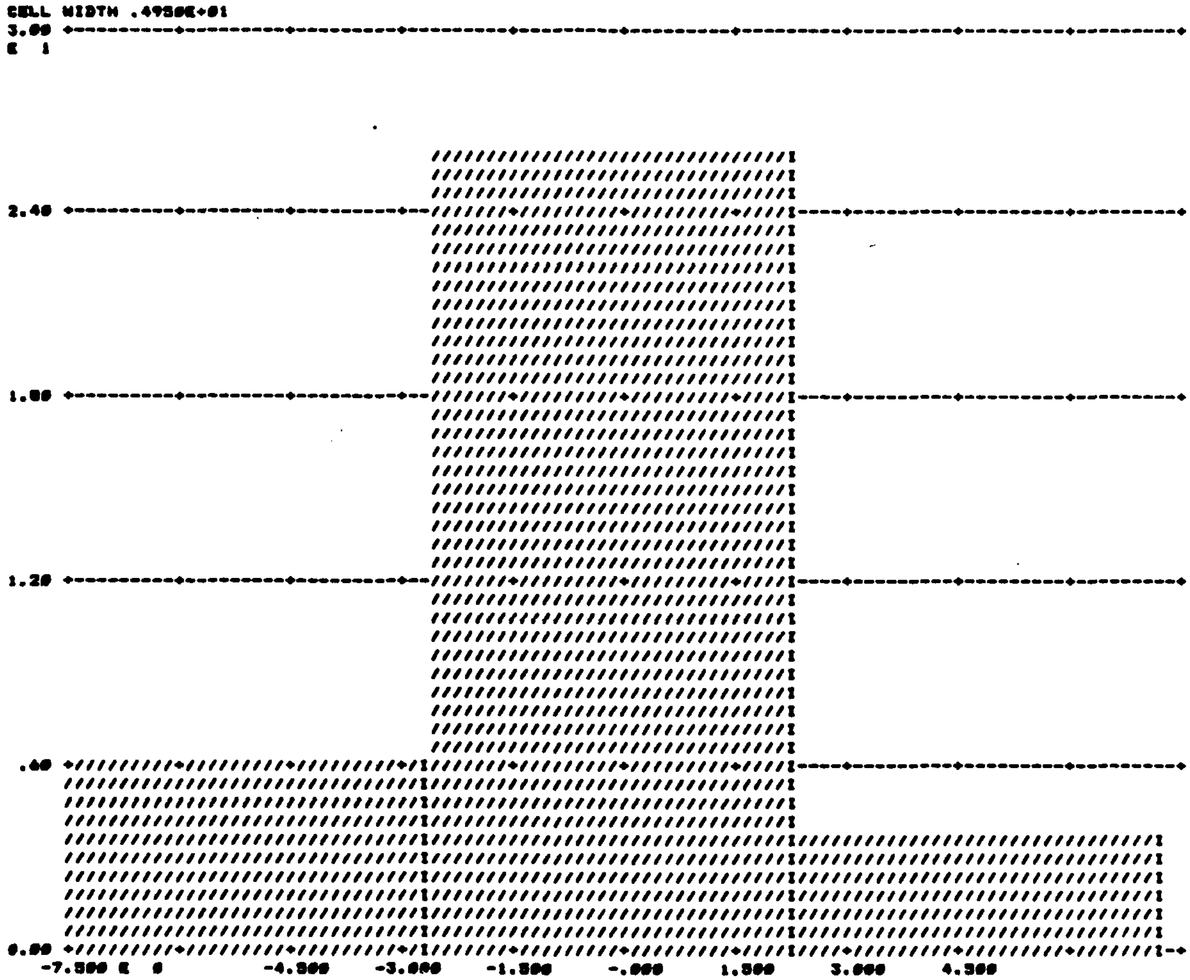


Figure C5

Cross Correlations
WUC:42GBØ Charger AC Battery

SERIES 1 - PREWHITENED ACTUAL FLYING HOURS
SERIES 2 - THE ESTIMATED RESIDUALS

MEAN OF SERIES 1 = -.36460E-01
ST. DEV. OF SERIES 1 = .26281E+00
MEAN OF SERIES 2 = -.29950E+00
ST. DEV. OF SERIES 2 = .26763E+01

NUMBER OF LAGS ON SERIES 1	CROSS CORRELATION	NUMBER OF LAGS ON SERIES 2	CROSS CORRELATION
0	-.016	0	-.016
1	-.007	1	.009
2	-.127	2	.256
3	.000	3	-.263
4	.019	4	-.059
5	.049	5	.162
6	-.155	6	.106
7	.014	7	-.270
8	.065	8	.101

A - PREWHITENED ACTUAL FLYING HOURS
B - THE ESTIMATED RESIDUALS
CROSS CORRELATION FUNCTION RAB(K)

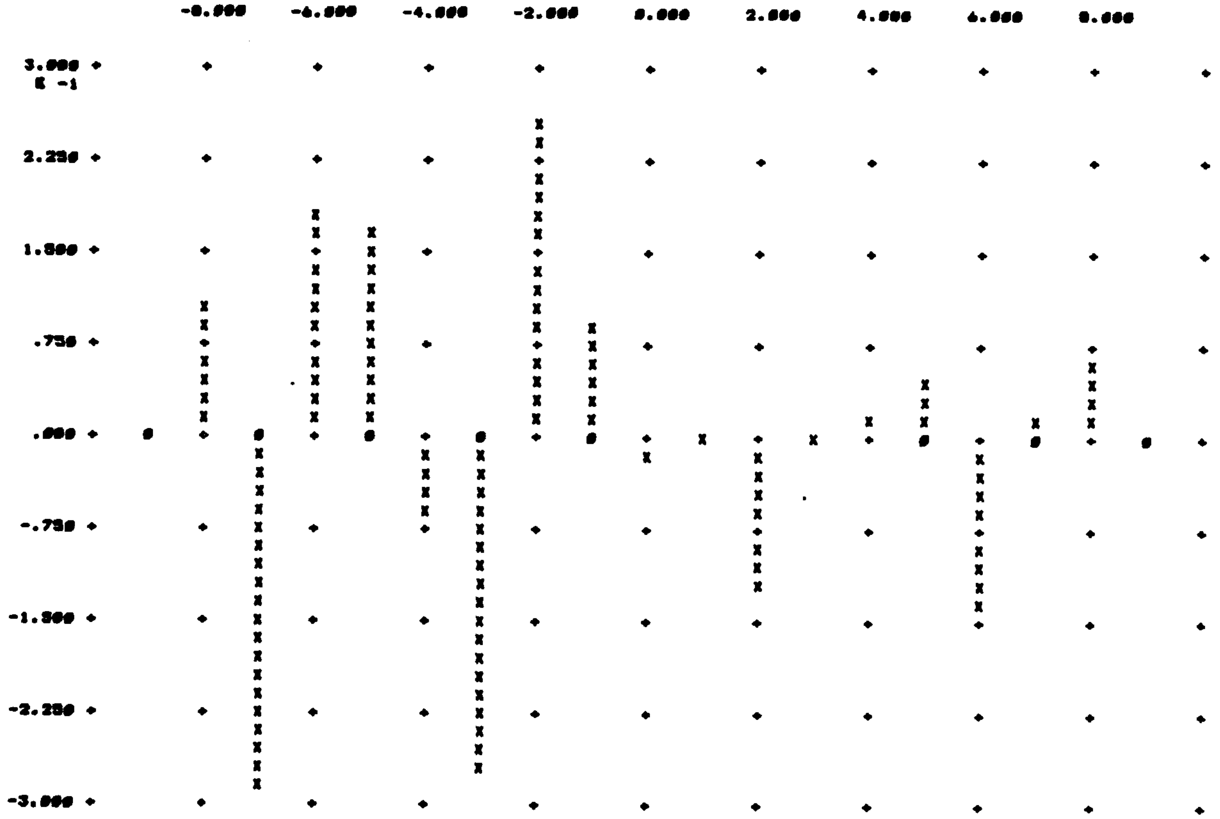


Figure C6

Estimated Impulse Response - WUC:24EBA PTO Shaft

X - Prewhitened Actual Flying Hours
Y - Prewhitened WUC:24EBA PTO Shaft

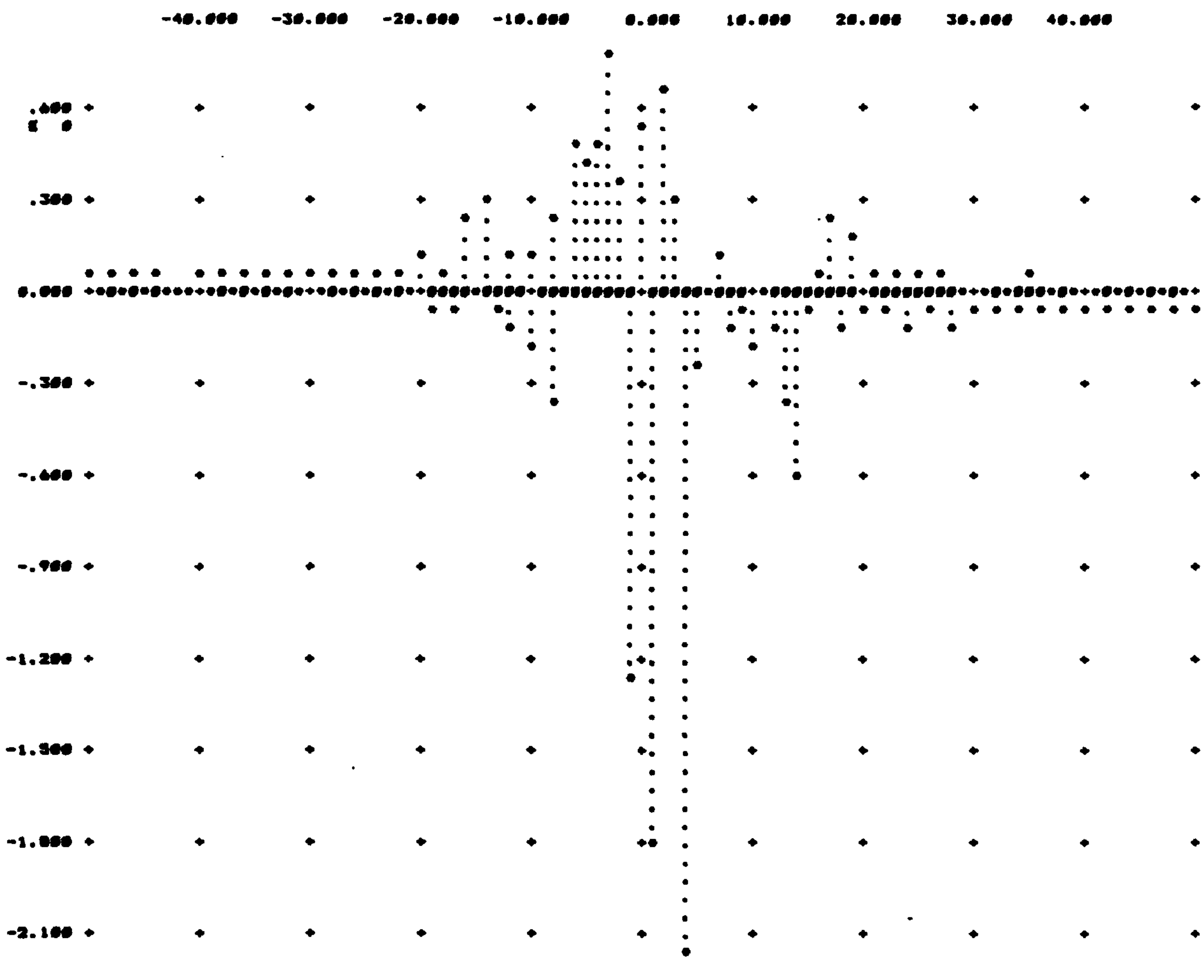


Figure C7

Summary of Model - WUC:24EBA PTO Shaft

DATA - X = ACTUAL FLYING HOURS   44 OBSERVATIONS
       Y = WUC:24EBA PTO SHAFT

DIFFERENCING ON Y - NONE

DIFFERENCING ON X - NONE

NOISE MODEL PARAMETERS

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT

TRANSFER FUNCTION PARAMETERS

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	OUTPUT LAG 1	1	.77362E-01	-.49133E+00	.64606E+00
2	OUTPUT LAG 1	2	-.13579E+00	-.69538E+00	.42380E+00
3	INPUT LAG 1	0	.79689E+00	-.11299E+01	.27237E+01
4	INPUT LAG 1	1	.14642E+01	-.40213E+00	.33306E+01
5	INPUT LAG 1	2	-.88371E+00	-.31504E+01	.13830E+01
6	INPUT LAG 1	4	.26610E+01	.61724E+00	.47047E+01

OPTIMUM VALUE OF B IS 0

OTHER INFORMATION AND RESULTS

RESIDUAL SUM OF SQUARES	.73874E+02	34 D.F.	RESIDUAL MEAN SQUARE	.21728E+01
NUMBER OF RESIDUALS	40		RESIDUAL STANDARD ERROR	.14740E+01

Figure C8

Periodogram - WUC:24EBA PTO Shaft

The Estimated Residuals
Cumulative Periodogram .1 Probability Limits

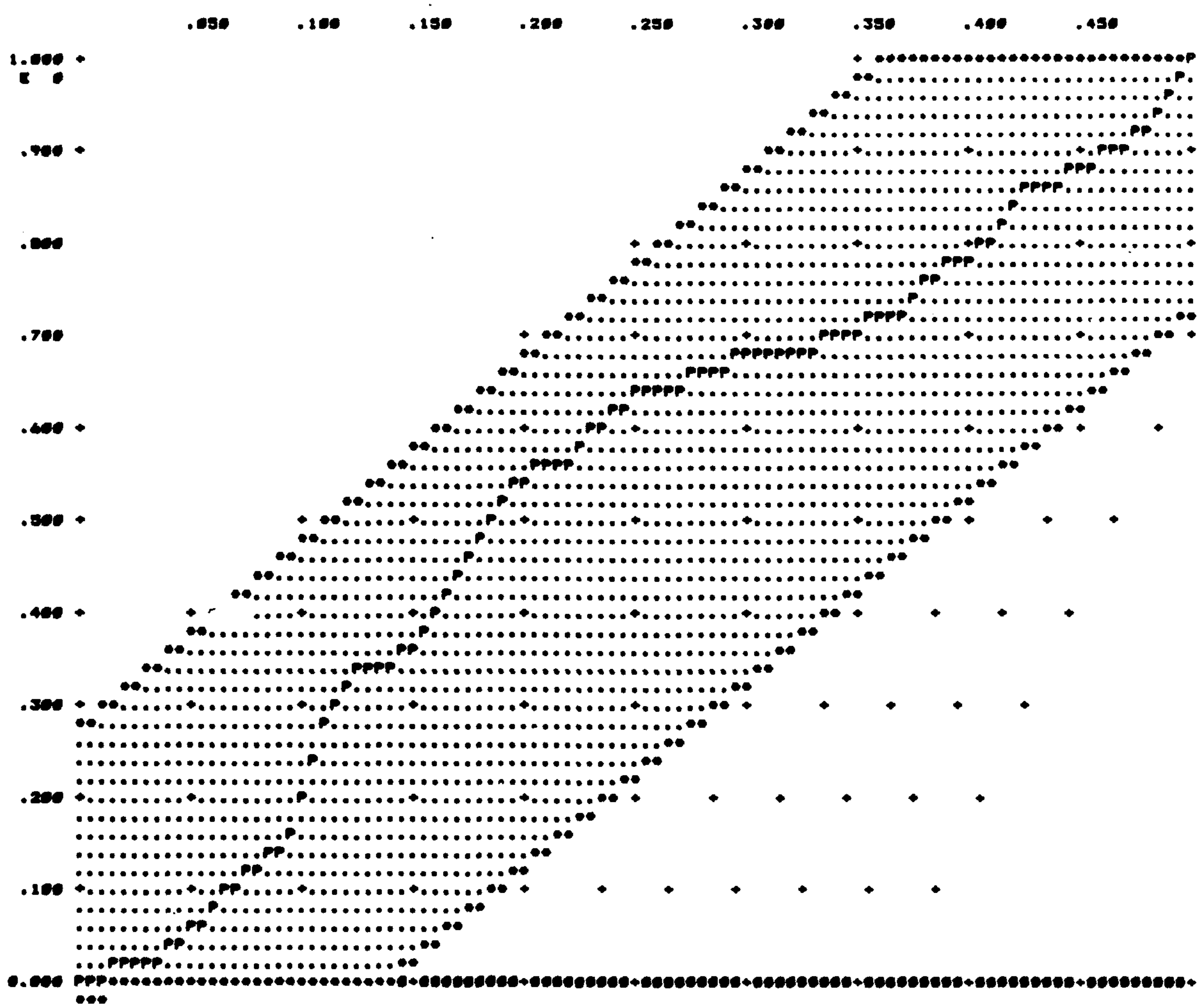


Figure C9

Histogram - WUC:24EBA PTO Shaft
The Estimated Residuals

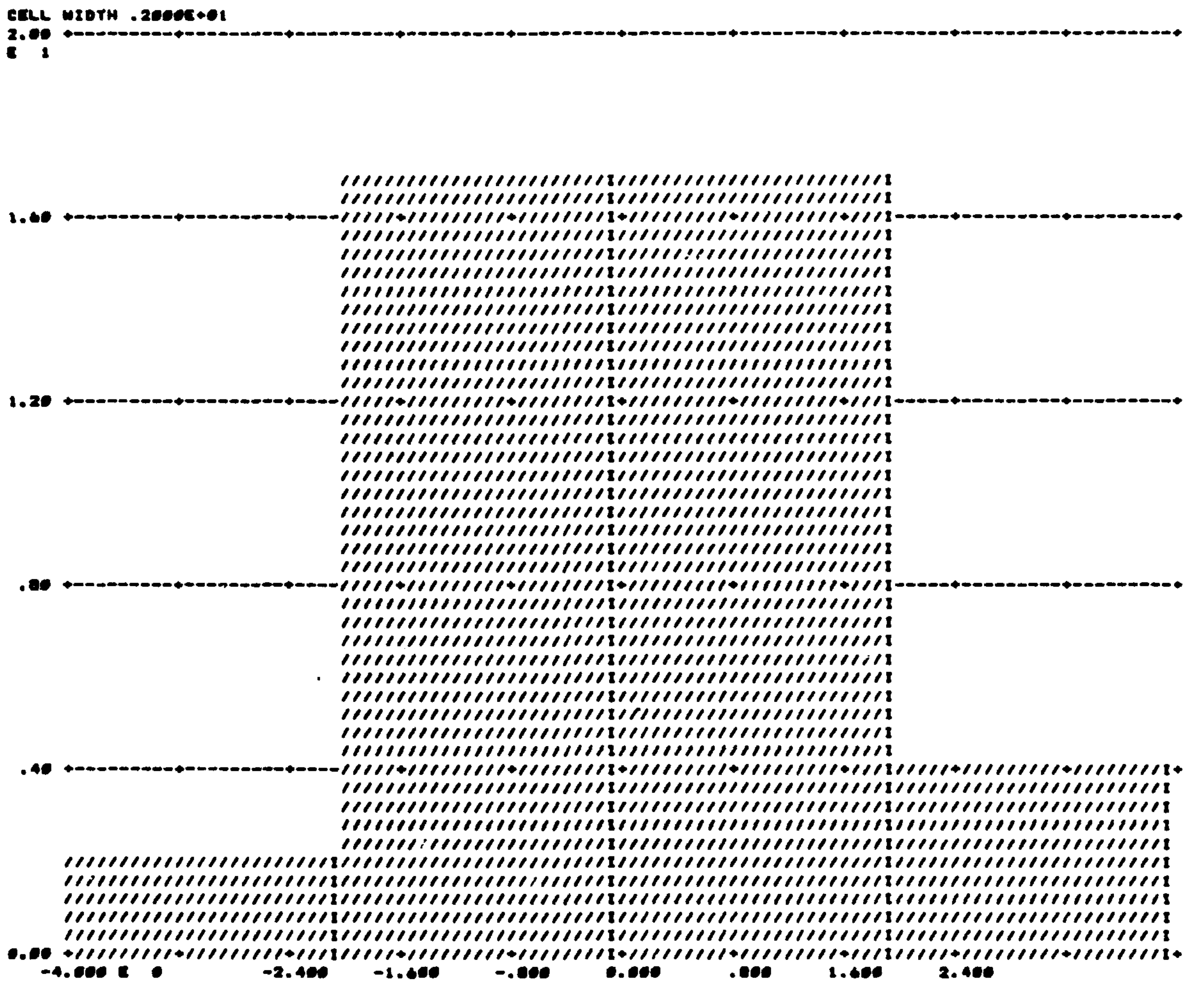


Figure C10

Cross Correlations
WUC:24EBA PTO Shaft

SERIES 1 - PREWHITENED ACTUAL FLYING HOURS
SERIES 2 - THE ESTIMATED RESIDUALS

MEAN OF SERIES 1 = -.20077E-01
ST. DEV. OF SERIES 1 = .25387E+00
MEAN OF SERIES 2 = .01808E-01
ST. DEV. OF SERIES 2 = .13565E+01

NUMBER OF LAGS ON SERIES 1	CROSS CORRELATION	NUMBER OF LAGS ON SERIES 2	CROSS CORRELATION
0	.005	0	.005
1	.010	1	-.265
2	-.004	2	.071
3	.020	3	.233
4	-.029	4	.081
5	-.016	5	.079
6	-.014	6	.033
7	-.021	7	-.141
8	-.086	8	.120

A - PREWHITENED ACTUAL FLYING HOURS
B - THE ESTIMATED RESIDUALS - WUC:24EBA PTO SHAFT
CROSS CORRELATION FUNCTION RAB(K)

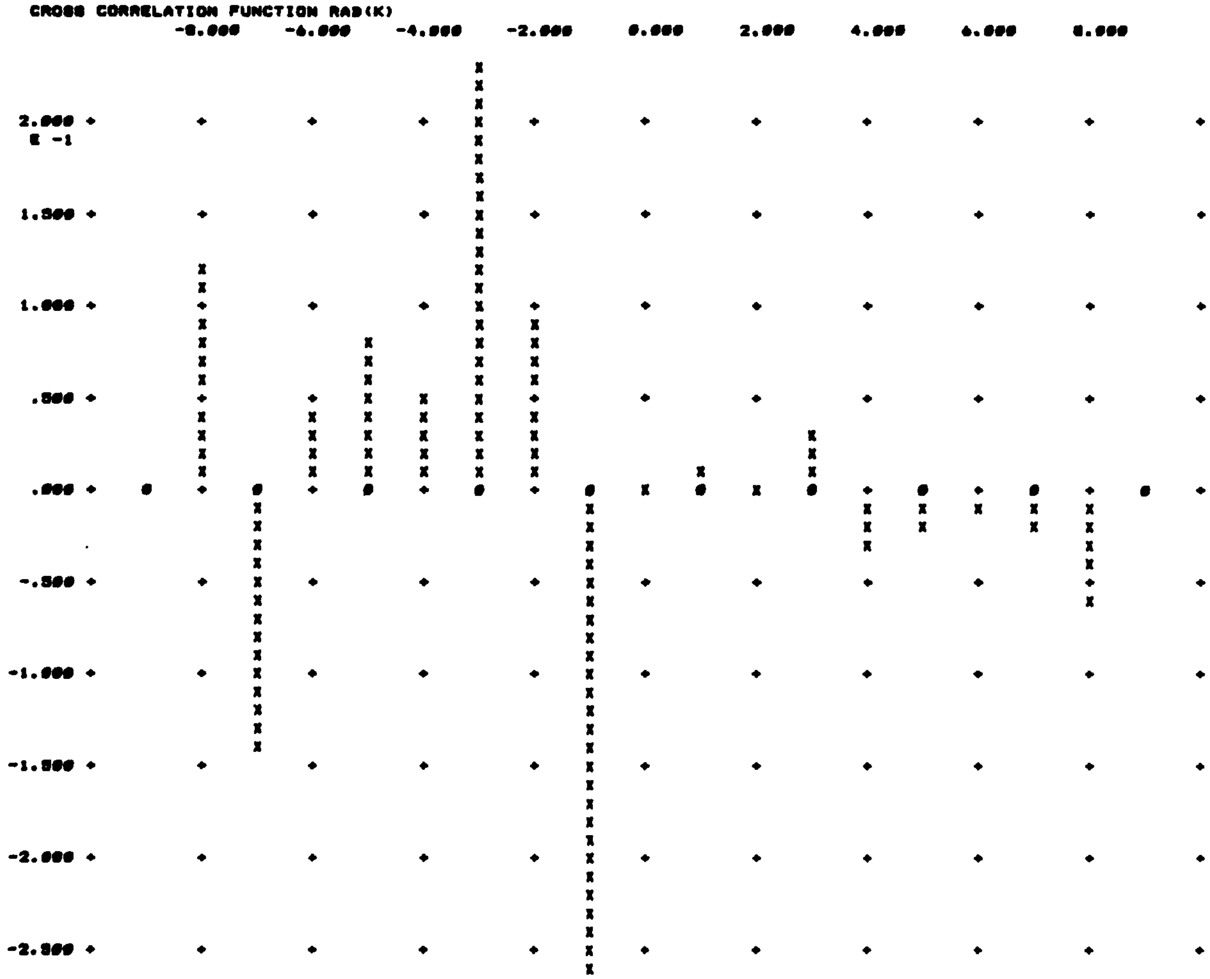


Figure C11

Estimated Impulse Response - WUC:46AFØ Proport Fuel Flow

X - Prewhitened Actual Flying Hours
Y - Prewhitened WUC:46AFØ Proport Fuel Flow

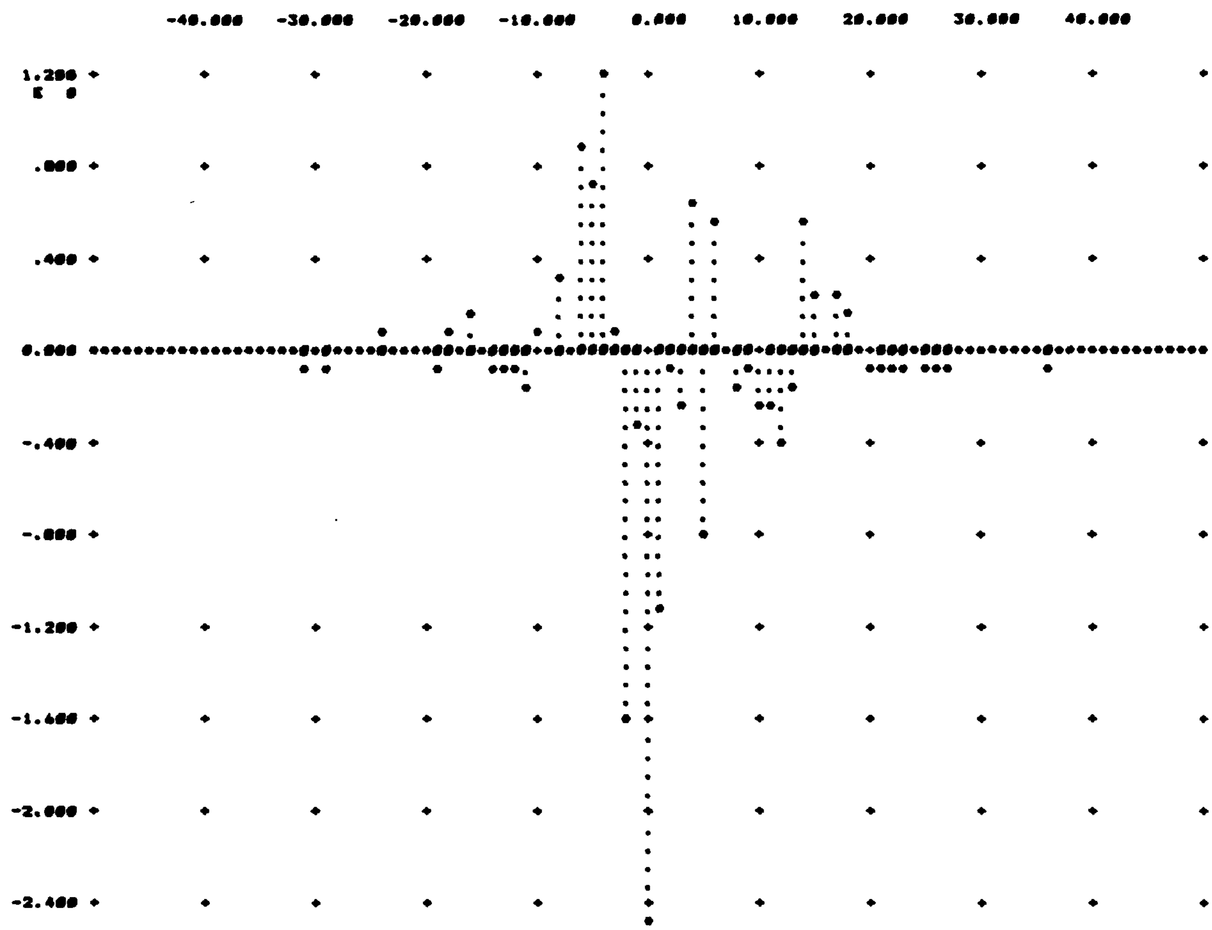


Figure C12

Summary of Model - WUC:46AFØ Proport Fuel Flow

DATA - X = ACTUAL FLYING HOURS
Y = WUC: 46AFØ PROPORT FUEL FLOW

44 OBSERVATIONS

DIFFERENCING ON Y - NONE

DIFFERENCING ON X - NONE

NOISE MODEL PARAMETERS

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	UPPER LIMIT

TRANSFER FUNCTION PARAMETERS

1	OUTPUT LAG 1	1	.35710E+00	-.57220E+00	.12866E+01
2	INPUT LAG 1	1	-.23915E+01	-.48686E+01	.85520E-01
3	INPUT LAG 1	5	.13710E+01	-.10402E+01	.37822E+01
4	INPUT LAG 1	6	-.13305E+01	-.38040E+01	.11430E+01

OPTIMUM VALUE OF D IS 0

OTHER INFORMATION AND RESULTS

RESIDUAL SUM OF SQUARES	.12326E+03	34 D.F.	RESIDUAL MEAN SQUARE	.36252E+01
NUMBER OF RESIDUALS	38		RESIDUAL STANDARD ERROR	.19040E+01

Figure C13

Periodogram - WUC:46AFØ Proport Fuel Flow
The Estimated Residuals
Cumulative Periodogram .1 Probability Limits

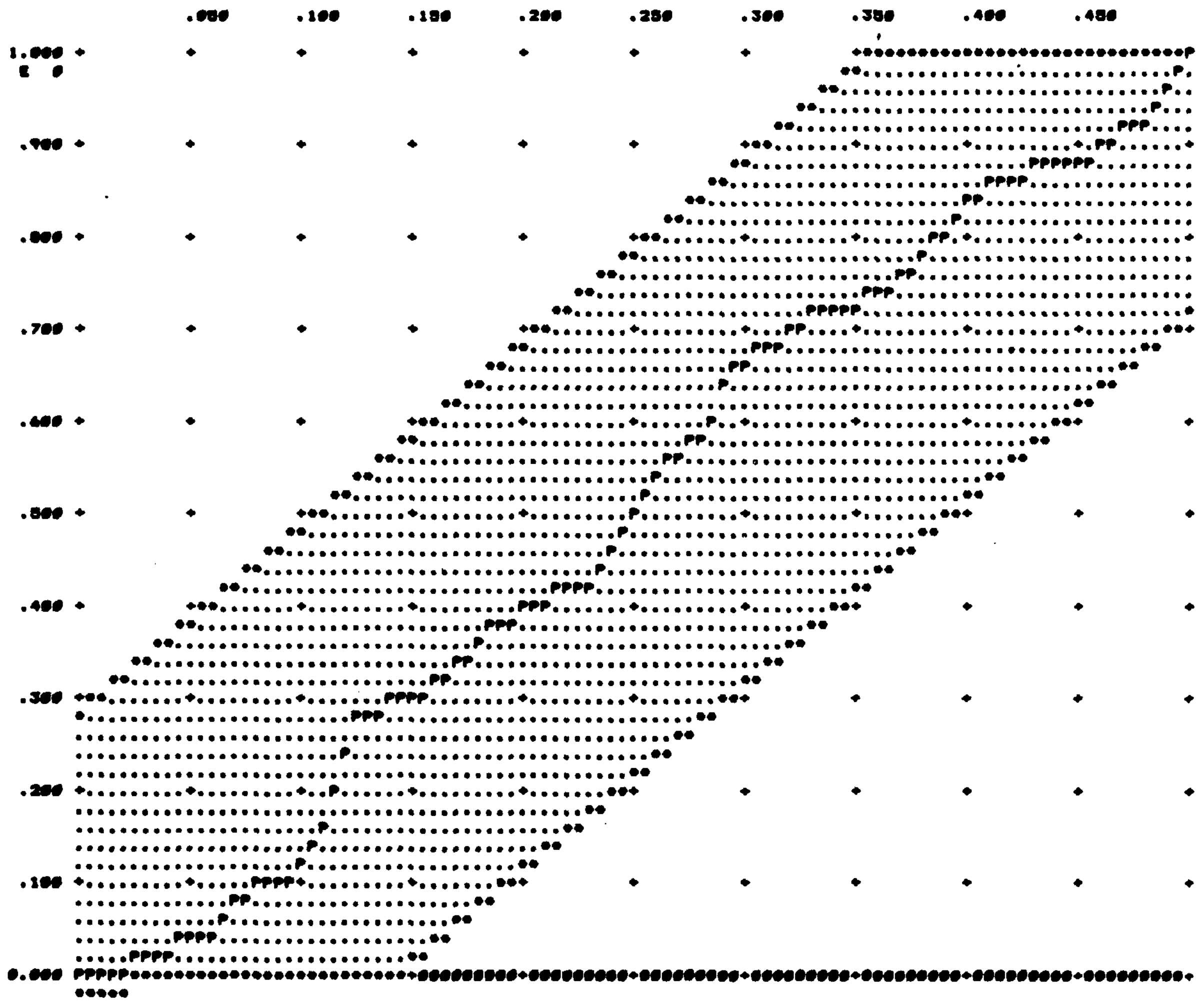


Figure C14

Histogram - WUC:46AFØ Proport Fuel Flow
The Estimated Residuals

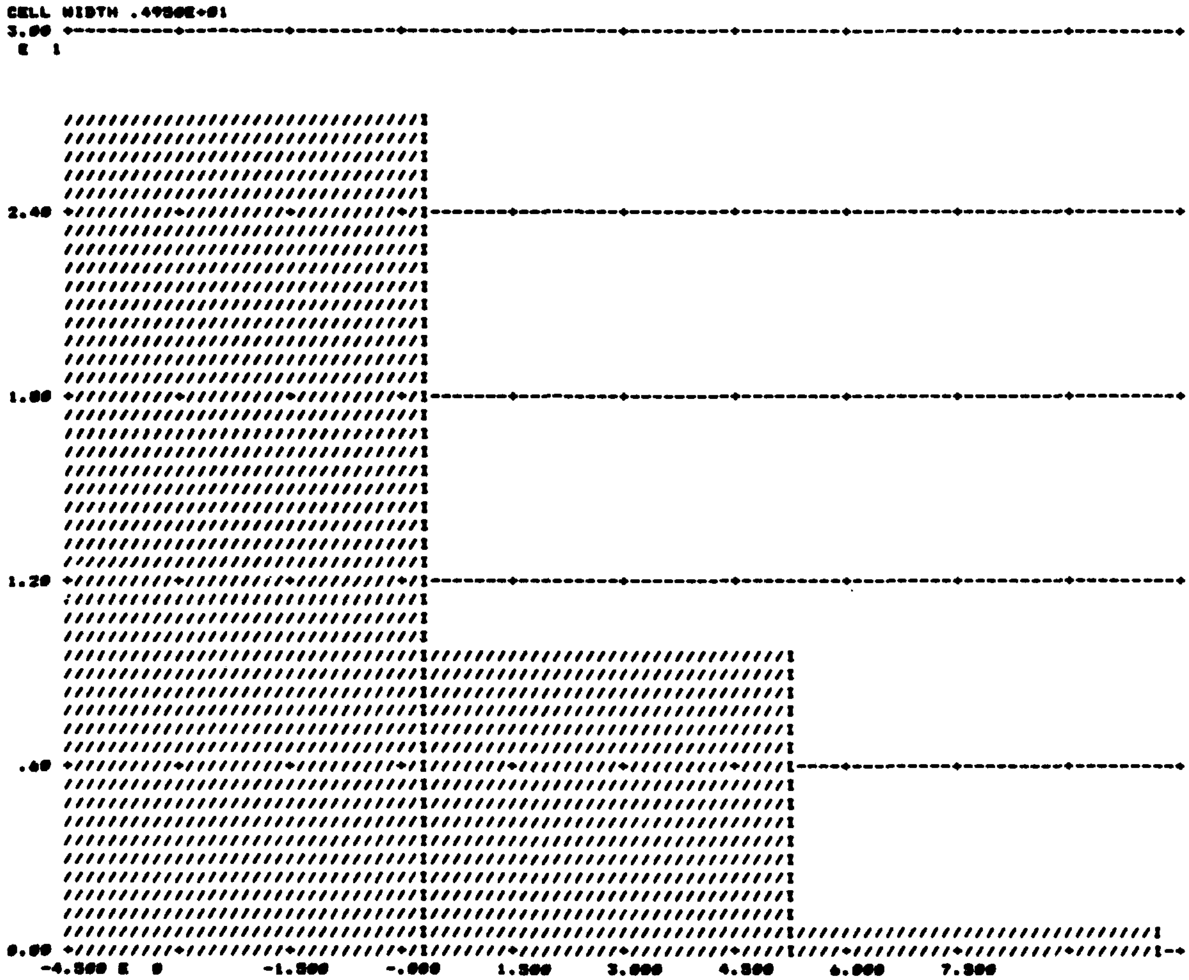


Figure C15

Cross Correlations
WUC:46AFØ Proport Fuel Flow

SERIES 1 - PREWHITENED ACTUAL FLYING HOURS
SERIES 2 - THE ESTIMATED RESIDUALS - MODEL 3

MEAN OF SERIES 1 = -.2778ØE-Ø1
ST. DEV. OF SERIES 1 = .2Ø821E+ØØ
MEAN OF SERIES 2 = -.8634ØE-Ø1
ST. DEV. OF SERIES 2 = .17989E+Ø1

NUMBER OF LAGS ON SERIES 1	CROSS CORRELATION	NUMBER OF LAGS ON SERIES 2	CROSS CORRELATION
Ø	.Ø12	Ø	.Ø12
1	-.Ø67	1	-.ØØ8
2	.Ø37	2	-.297
3	-.Ø81	3	.Ø26
4	.128	4	.246
5	-.ØØ9	5	-.ØØ4
6	.Ø28	6	.149
7	-.ØØ9	7	-.126
8	-.128	8	.Ø66

A - PREWHITENED ACTUAL FLYING HOURS
B - THE ESTIMATED RESIDUALS
CROSS CORRELATION FUNCTION RAB(K)

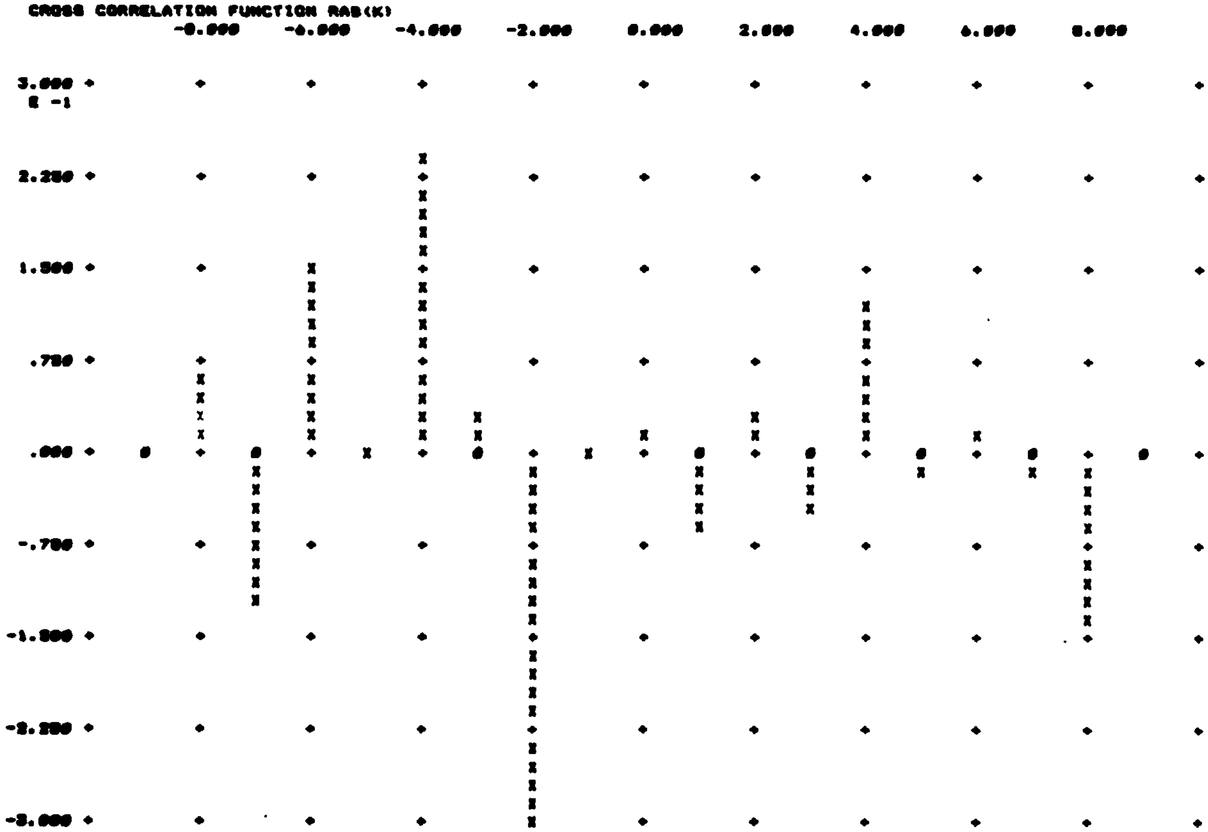


Figure C16

Estimated Impulse Response - WUC:46ANØ Vlv Shutoff Mot Opr

X - Prewhitened Actual Flying Hours
Y - Prewhitened WUC:46ANØ Vlv Shutoff Mot Opr

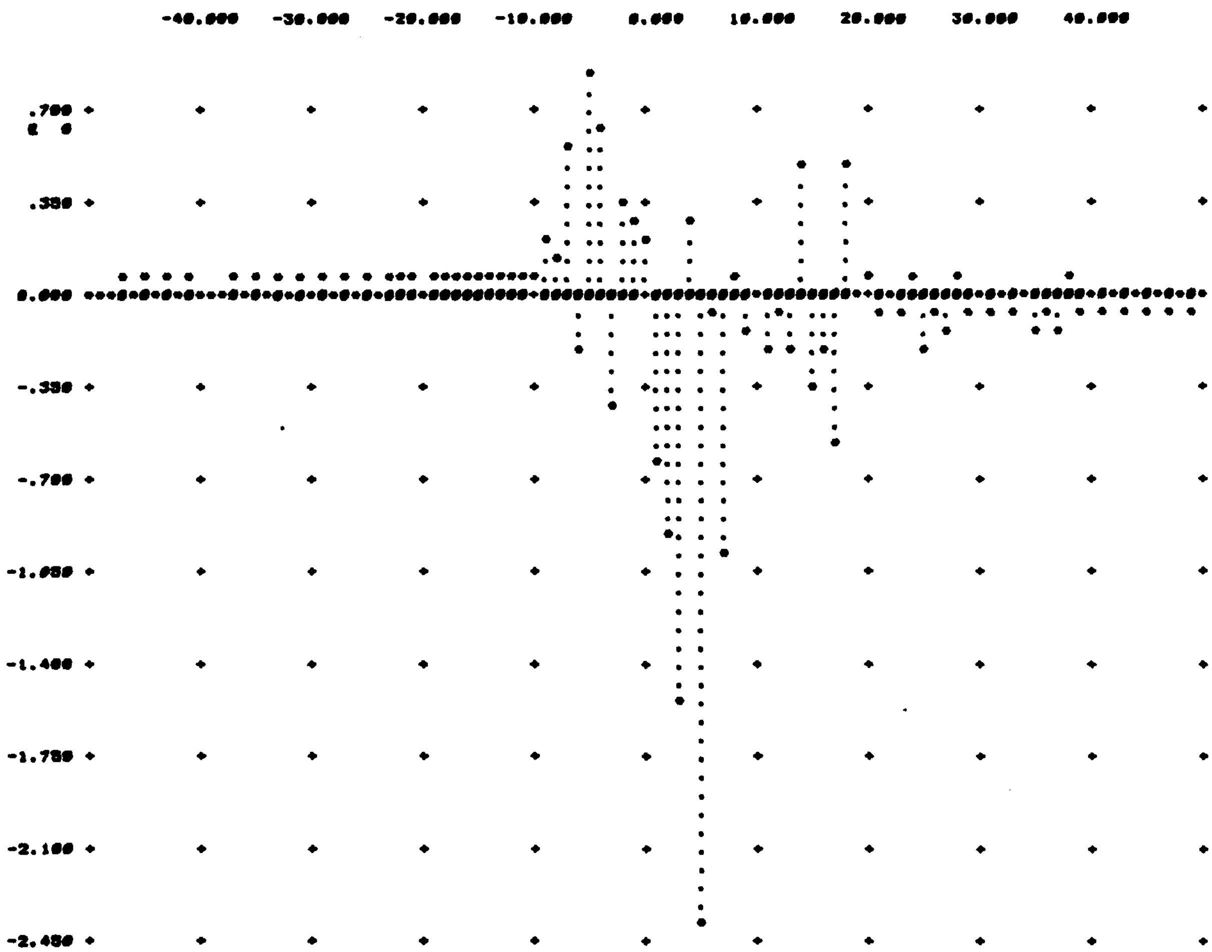


Figure C17

Summary of Model - WUC:46AN0 Vlv Shutoff Mot Opr

DATA - X = ACTUAL FLYING HOURS 44 OBSERVATIONS
Y = WUC: 46AN0 VALVE SHUTOFF MOTOR OPR

DIFFERENCING ON Y - NONE

DIFFERENCING ON X - NONE

NOISE MODEL PARAMETERS

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT

TRANSFER FUNCTION PARAMETERS

1	OUTPUT LAG 1	1	-.45490E+00	-.11324E+01	.22256E+00
2	INPUT LAG 1	0	.52943E+00	-.19041E+01	.29629E+01
3	INPUT LAG 1	3	.13670E+01	-.14300E+01	.41663E+01
4	INPUT LAG 1	4	-.61573E+00	-.36003E+01	.24400E+01
5	INPUT LAG 1	5	.22439E+01	-.10432E+01	.55310E+01

OPTIMUM VALUE OF B IS 0

OTHER INFORMATION AND RESULTS

RESIDUAL SUM OF SQUARES .16863E+03 34 D.F. RESIDUAL MEAN SQUARE .49597E+01

NUMBER OF RESIDUALS 39 RESIDUAL STANDARD ERROR .22270E+01

Figure C18

Periodogram - WUC:46ANØ Proport Fuel Flow
The Estimated Residuals
Cumulative Periodogram .1 Probability Limits

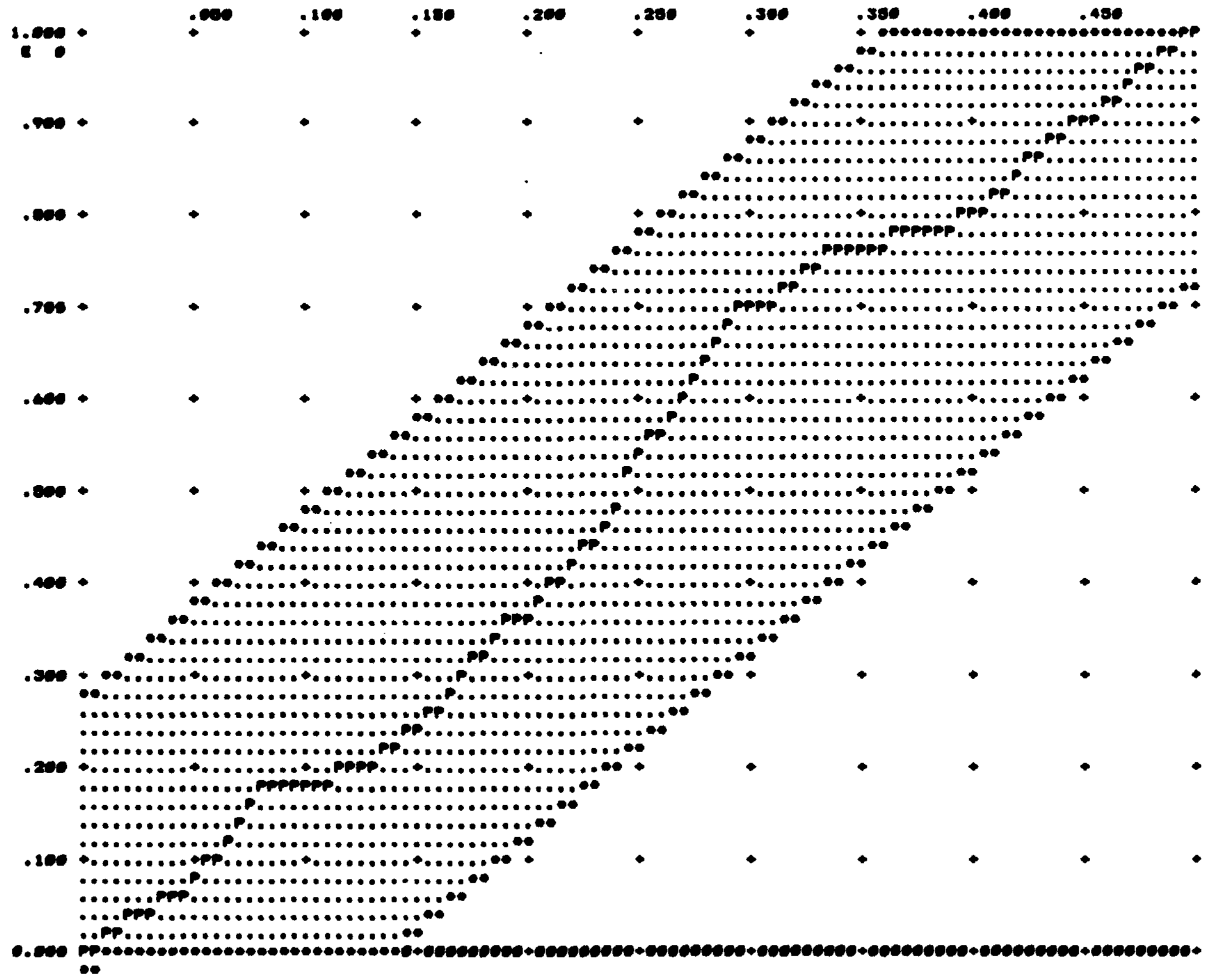


Figure C19

Histogram - WUC:46ANØ Proport Fuel Flow
The Estimated Residuals

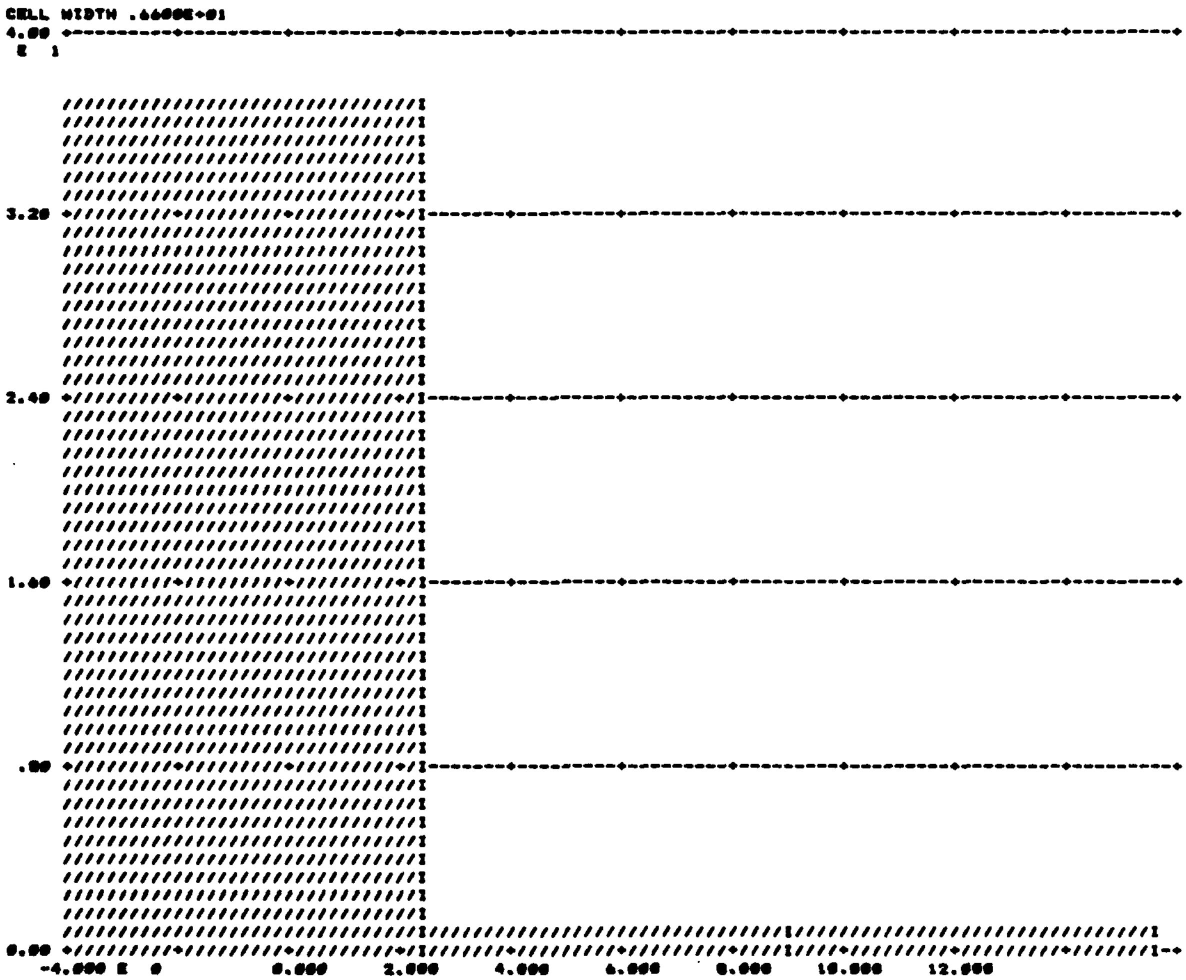


Figure C20

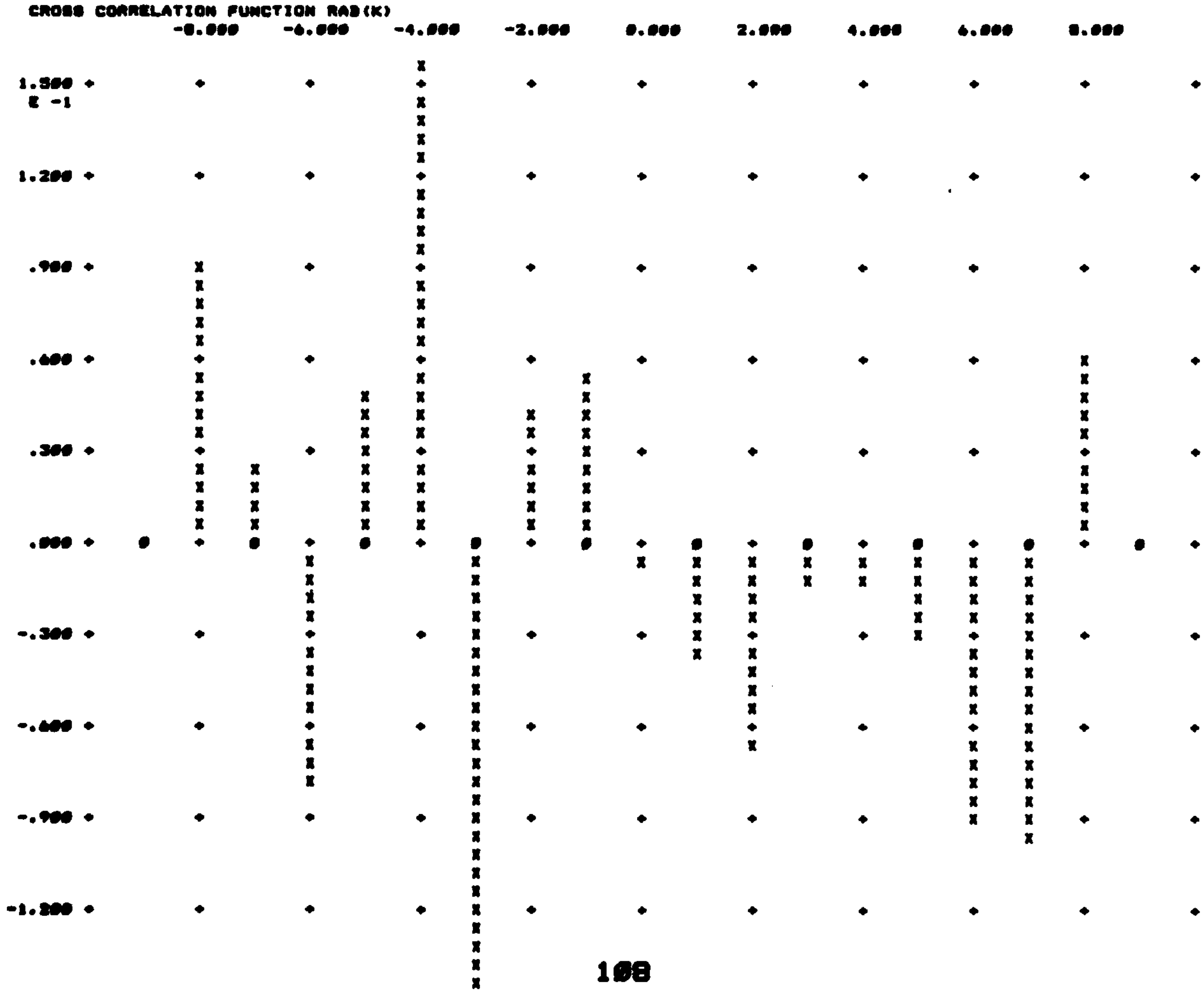
Cross Correlations
WUC:46AN0 Proport Fuel Flow

SERIES 1 - PREWHITENED ACTUAL FLYING HOURS
SERIES 2 - THE ESTIMATED RESIDUALS

MEAN OF SERIES 1 = -.23410E-01
ST. DEV. OF SERIES 1 = .25629E+00
MEAN OF SERIES 2 = .50040E-01
ST. DEV. OF SERIES 2 = .20780E+01

NUMBER OF LAGS ON SERIES 1	CROSS CORRELATION	NUMBER OF LAGS ON SERIES 2	CROSS CORRELATION
0	-.003	0	-.003
1	-.041	1	.054
2	-.066	2	.044
3	-.010	3	-.141
4	-.010	4	.155
5	-.029	5	.040
6	-.009	6	-.070
7	-.097	7	.023
8	.060	8	.000

A - PREWHITENED ACTUAL FLYING HOURS
B - THE ESTIMATED RESIDUALS
CROSS CORRELATION FUNCTION RAB(K)



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